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Simulating Nursing Unit Performance with OrgAhead: Strengths and Challenges

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Abstract

In this paper, we briefly describe our use of a computational modeling tool, OrgAhead, details of which have been reported previously, then discuss several of the challenges computational modeling presented and our solutions. We used OrgAhead to simulate 39 nursing units in 13 Arizona hospitals and then predict changes to improve overall patient quality and safety outcomes. Creating the virtual units required 1) collecting data from managers, staff, patients, quality and information services on each of the units, 2) mapping specific data elements (e.g., control over nursing practice, nursing workload, patient complexity, turbulence, orientation/tenure, education) to OrgAhead's parameters and variables, and then 3) validating that the newly created virtual units performed functionally like the actual units (e.g., actual patient medication errors and fall rates correlated with the accuracy outcome variable in OrgAhead). Validation studies demonstrated acceptable correspondence between actual and virtual units. For all but the highest performing unit, we generated strategies that improved virtual performance and could reasonably be implemented on actual units to improve outcomes. Nurse managers, to whom we reported the results, responded positively to the unit-specific recommendations, which other methods cannot provide. In the end, resolving the modeling challenges we encountered has improved OrgAhead's functionality and usability.

Keywords

Simulation; computational modeling; quality; safety; acute care nursing units

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,

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²In OrgAhead documentation, "accuracy" is referred to as "efficiency." However, the definition is more consistent with the term, accuracy; and efficiency is more consistent with what OrgAhead terms completion ratio. Therefore, we prefer using the more intuitive term "accuracy" to refer to OrgAhead's "efficiency" measure and have done so here. We do use the term completion ratio throughout the paper.

Conflicts of Interest None of the other authors reports any conflict of interest.

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to patients, the healthcare system, and society is extremely high. Valuable research findings related to patient safety and quality outcomes have yet to be implemented widely. Thus it was not surprising that Clancy challenged health services researchers to move beyond simply focusing attention on healthcare problems to identifying possible solutions for implementing needed action.¹

Contributing to the lack of improvement in healthcare safety and quality outcomes is the kind of performance feedback information that is available to managers. All too often managers are expected to integrate numerous data derived from a variety of non-integrated sources, e.g., clinical and financial databases. Frequently, many of the data elements are captured at single points in time, making interpretation and prediction beyond that specific point in time difficult. In addition, these data are rarely integrated across levels, making it difficult to see how organizational, unit, and patient variables interact within a particular context. As a result, managers faced with less than optimal patient outcomes often adopt the innovation “du jour” and then attempt to implement it across dissimilar patient care units or hospitals—frequently with widely disparate results.²⁻⁴ This kind of organizational trial-and-error management can be expensive in implementation costs, as well as in patient outcomes. Research findings indicate that general “one size fits all” changes in organizations are less effective, less acceptable to workers, and take longer to implement than customized changes that consider worker perceptions and organizational characteristics.⁵

Traditional analytic methods typically provide descriptive group level data (i.e., the mean levels of measured independent and dependent variables for a particular unit, compared with others in the sample). This type of data allows a manager to benchmark a nursing unit’s performance in terms of other units and may even suggest opportunities for change, but it is neither informative as to the effects of making a given change within that specific unit context nor does it point out the possible interaction effects from making multiple changes. Finally, this kind of data is not helpful in determining how much improvement in outcomes is likely to result from a given amount of increase in a specific independent variable. For example, if the manager initiates a change that increases nurses’ autonomy by 5 points on a reliable, valid instrument, how much impact can the manager expect to see on patient safety and quality outcomes?

One possible solution to these problems is computational modeling, sometimes referred to as computer simulation. The usefulness of computational modeling for building theory about organizational behavior and adaptation has been recognized for some time.^{6,7} Using computational modeling, researchers can create virtual organizations that correspond functionally 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 helps solve the problems cited above by enabling researchers to model complex systems, test the impact of multiple variables simultaneously, incorporate multiple levels of analysis (e.g., organization, unit, individual), and study the impact of organizational changes over time.⁸ Finally, computational modeling allows healthcare researchers to explore how contextual factors interact to constrain the impact of organizational changes on nurse practice patterns⁹ or patient outcomes.¹⁰

We have been using OrgAhead, a computational modeling program to simulate nursing units and then use the virtual units to test how nurse managers might improve quality and safety outcomes. After briefly summarizing our initial results, which have been reported elsewhere,^{11, 12} we discuss the challenges we have encountered in the initial (“Impact”) study and our current ongoing “DyNADS” project and how we have resolved them and, in doing so, improved the functionality and usability of OrgAhead.

Using OrgAhead

OrgAhead is a computational modeling tool developed by colleagues at Carnegie Mellon University in conjunction with Netanomics. Using OrgAhead, researchers can model the current performance of an organization and then, after validating the model against actual performance, test (in the virtual model) the potential impact of various changes on organizational performance.^{13, 14} Specifically, OrgAhead allows researchers to model organizational learning and performance over time, for example, examining how simulated changes in the organization's hierarchy, staffing levels, or task characteristics are likely to affect performance in the near and more distant future. OrgAhead can be used as a stand-alone system or as a sub-routine in the *ORA network analysis package, also developed by Carnegie Mellon colleagues and Netanomics. Some of the questions that OrgAhead can address include: 1) How do various constraints (e.g., size, the number of resources staff can manage, and how much history or memory each staff member can retain) affect organizational performance? 2) Do structures of adaptive organizations (those that exhibit better performance) differ substantially from those that are maladaptive? 3) Does initial organizational training affect long term performance? (<http://www.casos.cs.cmu.edu/projects/OrgAhead/>).

OrgAhead typically models organizations as 3-level hierarchies (e.g., CEO, Manager, Analyst) in which a given agent receives information from subordinates or the environment related to a problem and then the top-level agent, or set of agents, makes the decision. Agents can only report answers to their superiors. There can be up to 15 agents per hierarchy level. The organization is presented with a set of decision problems that take the form of an array of 0's and 1's (the binary task condition) or an array of three digits, 1, 2, or 3 (the trinary task condition). In our application of OrgAhead, each of these arrays is considered a patient (or patient-related task). A decision rule establishes the correct answer a priori. Typically, the decision rule for the binary task is whether there are more 1s or 0s (i.e., majority classification). For the trinary tasks, the decision rule is a function of the product of the array elements. The larger the array size, the more difficult it is to make an accurate decision. Answers can be yes/no (for binary choice problems) or yes/maybe/no (for the more difficult trinary choice problems). In the clinical setting, these tasks are analogous to deciding whether a patient is getting better or worse (in the binary task) or getting better, worse, or staying about the same (in the trinary task). Organizations may have greater or fewer resources (see more or less of each string), or more organizational memory (have previously encountered a larger number of patients). Depending on memory capacity and experience, organizations will learn to provide the correct answers—at least most of the time. After the final decision, all agents receive feedback as to the correctness of their responses. Organizational performance (or accuracy) is measured as the percentage of the virtual organization's responses that are correct (i.e., matches the decision rule). Note 1 The organization is simulated over a large number of tasks, typically tens of thousands, so that 1) the organization has sufficient opportunity to learn to the best of its ability, as limited by its constraints and structure; and 2) the performance of the organization becomes stable enough to be conclusive. Researchers can use the simulation results to inform several stages of virtual experimentation aimed at identifying what changes (e.g., increasing or decreasing specific staff positions, increasing training or resources; or decreasing task complexity) improve performance. These changes can be introduced individually or in combination.

We were the first research team to use OrgAhead in health care. Our ultimate goal is to develop a simulation tool that would allow nurse managers (and eventually other healthcare managers) to create virtual models of their units and then test the likelihood that changes

¹Neither OrgAhead nor *ORA are acronyms.

they might make would improve quality and safety outcomes such as patient falls or medication errors. To summarize briefly here, in the Impact study, data were collected from 32 nursing units in 12 acute care hospitals in Arizona. 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. To ensure a more comparable analysis across units, only adult medical or surgical units were included in the sample. We used the collected data to create virtual units that mapped well onto the actual units in terms of their functional (safety and quality) outcomes and then generated, for each of the nurse managers, a report that advised them which kinds of changes would be most likely to improve safety and quality outcomes on their units. Nurse managers found the recommendations extremely helpful in deciding what changes to make—or not make.^{11, 12}

The results of the descriptive analyses, path analyses, and linear regressions done as part of the Impact study provided managers with general insights into opportunities for innovation. With descriptive data, managers were able to compare their own mean scores on each variable with those of other units. The results of path analysis and linear regressions identified patient and unit characteristics significantly related to safety and quality outcomes. By extrapolating between the magnitude of their unit scores on each variable and the importance of the variable to quality and safety outcomes, it was possible for managers to identify potential areas to target unit change. However, these data did not provide the managers with any way to predict the potential effectiveness of targeting specific areas for change; but computational modeling did.

Computational modeling adds value to the researcher's arsenal in two different ways. First, it provides a way to model the complexity and cross-level interactions of an organization. We were able to create virtual units that corresponded functionally to actual units and then run experiments in which different values of key variables were entered and their relative effect on patient safety and quality outcomes assessed. Although most of our data were unit level, we were able to base the unit structure on the individual staff who worked there, and also incorporate patient risk factors. Although we have not yet done so, it is possible to incorporate organizational-level variables as well.

Second, computational modeling allows researchers to make predictions about the kinds of innovations that might improve performance outcomes and, through further virtual experiments, estimate the amount of improvement that can be expected with each innovation, which then can be shared with nurse managers. These unit-specific data provide managers with a basis for evaluating which factors might be the most important to improve, based on their unit's actual data or the relative impact on the desired outcomes. Clearly, it is much more cost effective and less chaotic to test the impact of unit changes in a virtual environment before implementing on an actual unit, provided the mapping from the real world to the virtual simulation is accurate enough. We did not attempt to include costs in our modeling but that too can be done.

A key strength of OrgAhead is its theoretical underpinnings, which contribute to its ability to accurately model reality using a limited set of variables. The results we provided to nurse managers in the Impact study resonated with their experience and intuitions. In addition, the managers found the data useful for planning purposes. Because, in some cases, up to two years had elapsed from the time in which the data were collected to when we were reporting simulation results, some unit changes had already occurred. In those cases where the change was one that we had modeled, managers were able to provide some validation for the predicted outcomes. For the highest performing units, we were able to tell them what changes not to make—and the managers perceived this as equally valuable.

In sum, computational simulation is a valuable tool that allows researchers to create virtual organizational models that correspond functionally to actual organizations and then to generate predictions about the impact of changing particular organizational characteristics. When combined with traditional analytic tools, these simulations provide actionable information to managers that can enable them to make intelligent, data-based changes on their units that have the best chance of improving patient safety and quality outcomes. Because we were adapting OrgAhead to a new domain, we encountered a number of challenges, both in the initial study, which was essentially a feasibility study, and in our current project, which aims to simplify the approach such that OrgAhead can become a simulation tool that managers can use themselves. In the following section we describe the challenges we have encountered along the way and how we resolved them.

Challenges and Solutions

Challenge 1. Mapping the variables

In our initial study, we collected data (based on current research) from nursing units to identify the hospital, patient and nursing unit factors that affect patient safety and quality outcomes (our first study aim). Doing so involved collecting a very large set of data from nursing staff, patients, nurse managers, quality management, and information services. We identified a set of variables that nurse managers could reasonably be expected to be able to modify that were most likely to affect the patient outcomes we were examining (nursing unit fall and medication error rates; and, for patients ready for discharge, their self reported satisfaction with care received, as well as their estimated simple and complex self care ability, and their estimated symptom management capabilities). With these results, we intended to simulate virtual units, using OrgAhead, so that we could use predictive modeling to identify, for each unit, the most promising and practical changes to improve outcomes.

The OrgAhead simulation has two major outcome variables: accuracy and completion ratio. Accuracy is defined as percentage of tasks for which the team provided the correct answer. Completion ratio is defined as the degree to which agents (and the organization) have the resources required to make accurate patient decisions.¹² Ultimately, we mapped safety outcomes onto accuracy and quality onto completion ratio. OrgAhead has a number of parameters, or input variables, which required much care in setting because we wanted the model to accurately reflect the nursing units. We spent considerable time defining the data variables and identifying the relevant OrgAhead variables and then mapping one onto the other. In some cases, we used composite variables that made sense conceptually to map onto an OrgAhead variable or parameter. See Table 1 for the variables mapped in the initial Impact Study.

During the mapping process, we found that a number of our research variables seemed to relate to the complexity of the work in which nursing staff were engaged. Because task complexity appeared to be a generic construct that could be useful in many settings, it was added to OrgAhead's repertoire. In the end, Task Complexity incorporated patient characteristics (i.e., Number of Comorbidities, Age, and Insurance) that, in our data, were important predictors of patient safety outcomes. Task Complexity also included unit characteristics such as Turbulence that were found to be predictive of patient safety outcomes and assumed to contribute to the complexity of care. Our experience suggests that when OrgAhead is applied outside of the domain for which it was initially intended, careful attention must be paid to the mapping of available data to OrgAhead variables.

Challenge 2. Validating the model

Validation is an important step that frequently is omitted by researchers, but is essential if the simulation results are to be trusted. Our validation procedure in the Impact study entailed

comparing the observed total reported medication errors and falls (with and without injury) for the 32 units with their corresponding accuracy (efficiency) measures in OrgAhead. In addition, we compared performance on quality outcomes (Simple Self Care, Complex Self Care, and Symptom Management) with the corresponding OrgAhead variable, Completion Ratio. For each of the units, values of Task Complexity, Standard Operating Procedures (SOP), and Training Period variables were set based on the observed data. These particular variables were selected for testing because causal modeling showed they had a statistically significant impact on medication errors or patient falls. Although the number of staff simulated varied according to the actual unit data, we kept the amount of information each hierarchical level (i.e., RNs, LPNs and Patient Care Technicians [PCTs], and Unit Clerks) could access the same, and also kept the hierarchical structure the same across units. We then rank ordered the virtual and actual performance measures and compared them using correlation statistics. The correlation of safety outcomes with accuracy was surprisingly high (.83) for this type of work; and the correlation of quality outcomes with completion ratio was also acceptable (−.62).¹² Typically, validation can be done using either the actual performance values or the rank order of unit performance. Our sample size in the Impact study allowed us to use both metrics. In our current DyNADS study, our sample size is much smaller (7) so we are limited to rank order correlations.

Challenge 3. Streamlining data collection

Our ultimate goal is to put a simulation tool on nurse managers' desks. In the Impact study, we had collected a variety of data based on published research about possible hospital, unit, and patient variables that might affect patient outcomes on nursing units. We recognized that hospitals could not reasonably be expected to collect this amount of data. Therefore, we needed to streamline data collection considerably. This became an explicit goal of the DyNADS study. To achieve the goal, we collected essentially the same data as in the Impact study (with the addition of managerial support, which was based on new research findings) so that we could compare the full data set with the streamlined version to ensure that it was functioning equally well. We developed a novel procedure for streamlining that reduced the number of staff variables from the original 158 to 74.¹⁵ Because some of the initial data we had collected were not being used in the simulation, we were able to further reduce the number of scales by 4 and the number of items to be collected from nursing staff to just 32. To compare the initial and streamlined data sets, correlations were run between the OrgAhead safety and quality metrics using the original set of variables and the streamlined set of variables. For the safety variables, the correlation was .82; for the quality variables, the correlation was .98. Thus, the streamlined set of variables was as effective as the full set of variables.¹⁶ In the DyNADS study, we also assessed, as part of a cognitive work analysis, precisely what data hospitals are already collecting from patients and staff that might reduce the need for additional data collection.¹⁷ Future studies will be needed to determine the extent to which these hospital data can be substituted for the survey data we have been collecting. Given the recent focus on aligning outcome data across agencies to facilitate both collection and comparative analysis,¹⁸ this will be extremely important.

Challenge 4. Generalizing the model

We had built our initial simulation on the basis of the 32 units in the Impact study. In our current DyNADS study, we have only seven units and are using the streamlined set of data for modeling. The small number of units has made it impossible to use composite variables comprising multiple data elements, which were defined in the Impact study based on relationships in a factor analysis. Therefore, we had to go back to the mapping step and reconfigure the model. Table 1 compares the OrgAhead variables used in the initial (Impact) study with those used in the current (DyNADS) study. As we mapped variables, we discovered that OrgAhead had been configured using the data ranges and relationships

collected in the Impact study. If the model were to be generalizable beyond a given set of units, we would need to normalize the data used for input variables and rescale the normalized values to a range that fit within OrgAhead's acceptable values.¹⁹ Ultimately this process also required modifying the simulation algorithms and reprogramming the applications so that the results would generalize to any sample.

Challenge 5. Increasing the usability of OrgAhead

Computational modeling tools, such as OrgAhead, were developed for organizational and simulation researchers. The language used in OrgAhead is not at all familiar to health care professionals. Therefore, we have had to modify the simulator language to be more easily understood—without losing all meaning for researchers, programmers, and others. Similarly, the terms used by the nurse researchers on the team were not always understandable to the technical members of the team so we have spent additional time defining these terms. In the future, we intend to conduct a variety of usability studies with anticipated DyNADS users to determine whether the current terminology is understandable.

Challenge 6. From hierarchy to network

OrgAhead's structural model is that of a simple 3-tiered hierarchy in which the chief executive is at the top and makes the final decision based on the judgments of the persons reporting to him. In the Impact study, the hierarchy was modeled such that RNs were the final decision makers, followed by patient care technicians and LPNs, then unit clerks. This was problematic for several reasons. Initially, the number of staff made the model too large for OrgAhead to process; the application could not run. To counter this, we ultimately ran the model with 1/3 of the actual staff. Additional optimization of the model has helped, but we are still running the models with 1/2 the staff—something we ultimately hope to resolve. Second, the hierarchical model didn't reflect reality; nursing units are typically structured as several smaller teams and appeared to be much more decentralized than the hierarchy indicated. Further, we had created the hierarchical structure we used based on intuition and experience, but not on data. Unit clerks have a unique set of information and are central figures to the general management of the unit—but do not fit well into the direct patient care configuration. In the DyNADS study, we are experimenting with incorporating a network communication model, based on empirical staff network data, and deriving the hierarchical structure from the network model.²⁰ This too is challenging. First, we had to integrate *ORA, the network analysis tool, with OrgAhead, which required extensive programming. Second, we had to determine how to derive the OrgAhead hierarchy from *ORA. Although *ORA has within it a hierarchy measure that can even be visualized, that didn't mean that it would be usable within OrgAhead. The data for *ORA were collected by shift on two separate days; we had to determine whether to model by shift or by day. We decided to start with shift for the day with the best response rate to minimize gaps in the network. When multiple staff communicated with others, we needed to devise some type of heuristic or algorithm to break ties (as when 2 RNs and 2 PCTs reported to another RN). All of this has required extensive work by both the *ORA and OrgAhead programmer/analysts. Several technical reports have been written to document the thinking and changes made to the model. Despite these changes, OrgAhead still uses a hierarchical model.

Challenge 7. Matching the problem set to nursing units

When we were able to increase the number of staff in the OrgAhead hierarchy without compromising performance, we simultaneously lost the variability in performance because now the underlying computer task measuring organizational performance was too simple, given the additional human resources available to solve it. Therefore, we adopted the more complex trinary task.

Challenge 8. Modeling takes time

The Impact study (from data collection to reporting) took over two years because of the mapping, calibration, fine tuning, and virtual experiments that were needed before we could report our findings and recommendations to nurse managers. This turned out to be both problematic and serendipitous. Some nurse managers had changed positions; and some units had changed radically in terms of location, patient population, or physical configuration, which made our recommendations less timely than ideal. However, some of these unit changes were fortuitous because they mirrored our recommendations and therefore served as informal use cases in which to test the validity of our predictions. Even in the DyNADS study, the simulation process has taken more time than anticipated because the streamlined variables necessitated changes to the computational model which, in turn, have required alpha and beta testing with the actual data. OrgAhead allows batch execution, so we now can run sequences of virtual experiments in which we vary multiple variables stepwise so that we can determine the most effective combination of changes to improve outcomes. Clearly, conducting the experiments one at a time is not the most efficient way to accomplish this.

Challenge 9. The need for more specificity

OrgAhead has only two performance measures, accuracy and completion ratio. In each study, we mapped multiple actual outcomes onto each of these. However, the variables that can be changed within OrgAhead are more specific so that we could suggest to nurse managers that modifications in nursing culture would likely be more helpful than increasing staff, for example. This procedure has been problematic in the second study because performance on the two safety outcomes (medication errors and patient falls) varied radically among the seven units; and consequently, an intervention that might reduce patient falls might potentially increase medication errors. Further research will be needed using a much larger sample to see if this issue persists. Ultimately, we hope to modify the tool so that we can provide more detailed recommendations.

Conclusion

We have described our use of OrgAhead, a computational modeling simulation tool initially developed for business applications, to healthcare. In our initial application of the tool (the Impact study), we used data collected from 32 units to simulate virtual models of each unit and then used OrgAhead to generate predictions about what nurse managers might do to improve safety and quality outcomes. Our initial application of OrgAhead was more successful than we had dared to dream. We were able to validate the model and generate useful predictions. However, we encountered challenges at each step of the process. Our second application of OrgAhead (the DyNADS study) has presented new challenges because of the smaller sample size, differences in the streamlined data set, and the need to ensure that the model is sufficiently generic to be widely applied.

In summary, simulating organizations through computational modeling is a valuable tool for researchers that we are attempting to simplify in such a way that it can be put on the manager's desk. Ultimately, we anticipate that managers in a variety of settings will be able to test innovations and changes in a virtual world before they go to the time and expense of implementing them in real life. However, additional research and development are needed before it will be practical for use by non-researchers.

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References

1. Clancy CM. Health services research: From galvanizing attention to creating action. *Health Serv Res.* 2003; 38:777. [PubMed: 12822911]
2. Lynn MR, Layman E. The nature of nursing administration research. Knowledge building or fire stomping? *J Nursing Admin.* 1996; 26(5):9–14.
3. Sochalski K, Aiken LH, Fagin C. Hospital restructuring in the U.S., Canada, and Western Europe. *Med Care.* 1997; 35(10):S13–S25.
4. Walston SL, Urden LD, Sullivan P. Hospital reengineering: an evolving management innovation: history, current status, and future directions. *J Health Hum Serv Admin.* 2001; 23(4):388–415.
5. Prochaska JM, Prochaska JO, Levesque DA. A transtheoretical approach to changing organizations. *Admin Policy Mental Health.* 2001; 28(4):247–261.
6. Carley KM. Computational and mathematical organization theory: Perspective and directions. *Comput Math Org Theory.* 1995; 1:39–56.
7. Lant, TL. Computer simulation of organizations as experimental learning systems: Implications for organization theory. In: Carley, KM.; Prietula, KM., editors. *Computational Organization Theory.* Lawrence Erlbaum Associates; Hillsdale, NJ: 1994. p. 195-216.
8. Clancy TM, Effken JA, Pesut D. Application of complex systems theory in nursing education, research and practice. *Nurs Outlook.* 2008; 56(5):248–56. [PubMed: 18922279]
9. Clancy TM, Delaney CW, Segre A, Carley K, Kuziak A, Yu H. Predicting the impact of an electronic health record on practice patterns using computational modeling and simulation. *AMIA Ann Symp Proc.* Oct 1.2007 :145–9.
10. Effken J. Computational modeling: From virtual to actual. *Nurs Manage.* 2009; 40(3):31–4.
11. Effken JA, Brewer BB, Patil A, Lamb GS, Verran JA, Carley KM. Using computational modeling to transform nursing data into actionable information. *J Biomed Informat.* 2003; 36(4-5):351–61.
12. Effken JA, Brewer BB, Patil A, Lamb GS, Verran JA, Carley KM. Using OrgAhead, a computational modeling program, to improve patient care unit safety and quality outcomes. *Internat J Med Informat.* 2005; 74(7-8):605–13.
13. Carley, KM. Organizational adaptation in volatile environments. In: Ilgen, DR.; Hulin, CL., editors. *Computational Modeling of Behavior in Organizations: The Third Scientific Discipline.* American Psychological Association; Washington, DC: 2000. p. 241-73.
14. Lee, J.; Carley, K. *OrgAhead: A Computational Model of Organizational Learning and Decision Making.* Version 2.1.5. Carnegie Mellon University, School of Computer Science, Institute for Software Research International; 2004. Technical Report CMU-ISRI-04-117
15. Verran, JA.; Lim, K. A technique for streamlining data collection. *Proceedings of the Communication Nursing Research Conference; Portland, OR: Western Institute of Nursing; 2009.* p. 134
16. Verran, JA.; Brewer, BB. Validation of data streamlining with computational modeling. *Proceedings of the Communication Nursing Research Conference; Portland, OR: Western Institute of Nursing; 2011.* p. 112
17. Effken JA, Brewer BB, Logue MD, Gephart SM, Verran JA. Using cognitive work analysis to fit decision support tools to nurse managers' work flow. *Internat J Med Informat.* 2011; 80:696–707.
18. Damberg, CL.; Sorbero, ME.; Lovejoy, SL.; Lauderdale, K.; Wertheimer, S.; Smith, A.; Waxman, D.; Schnyer, C. *An Evaluation of the Use of Performance Measures in Health Care.* Rand Corporation; Santa Monica, CA: 2011. Available at http://www.rand.org/pubs/technical_reports/TR1148.html

19. Brewer, BB. Translating data from complex virtual environments to complex actual environments. Proceedings of the Communication Nursing Research Conference; Portland, OR: Western Institute of Nursing; 2011. p. 111
20. Effken JA, Carley KM, Gephart SM, Verran JA, Bianchi D, Reminga J, Brewer BB. Using ORA to explore the relationship of nursing unit communication to patient safety and quality outcomes. *Internat J Med Informat.* 2011; 80:505–17.

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Table 1

OrgAhead parameters and corresponding nursing unit variables in the initial IMPACT study and as modified for the current DyNADS study

OrgAhead Parameter	IMPACT Variable	DyNADS Variable
Training Period	Education	Hospital Tenure
	Experience	Unit Tenure
		Experienced RN Orientation
		New RN Orientation
		LPN Orientation
		PCT Orientation
		UC Orientation
Task Complexity	Leave *	Leave *
	Distance *	Distance *
	Environmental Uncertainty *	Environmental Uncertainty *
	Unresponsive Support Staff *	Unresponsive Support Staff *
	RN WorkLoad	RN WorkLoad
	Self Pay/Uninsured	Self Pay/Uninsured
	Elderly	Elderly
	Average Number ICD-9 Codes	High Complexity
	Patients per Day *	Patient Turnover
		Technology
Standard Operating Procedures	RN Control Over Nursing Practice	RN Control Over Nursing Practice
	PCT LPN Control Over Practice	PCT LPN Control Over Practice
	UC Control Over Practice	UC Control Over Practice
		Management Support
Hierarchy	RN FTE	RN FTE
	LPN FTE	LPN FTE
	PCT FTE	PCT FTE
	UC FTE	UC FTE
Memory		% Staff with Bachelor's Degree
	Estimated	% Staff with Continuing Education > 35 hours / year

* Components of Turbulence