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Evaluation in Health Informatics: Computer Simulation

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Introduction: Evaluation in Medical Informatics

The evaluation of complex medical informatics applications involves not only the information system, but also its impact on the organizational environment in which it is implemented. In instances where these applications cannot be evaluated with traditional experimental methods, computer simulation provides a flexible approach to evaluation. The construction of a computer simulation model involves the development of a model that represents important aspects of the system under evaluation. Once validated, the model can be used to study the effects of variation in system inputs, differences in initial conditions and changes in the structure of the system. Three examples are discussed, namely, a wide-area healthcare network, physician order entry into a hospital information system, and the use of an information system designed to prevent medical errors that lead to adverse drug events in hospitals.

Medical informatics applications are complex. They generally involve information technology that is implemented in a complex organizational setting. While technical aspects of these systems and user interfaces can be evaluated prior to implementation, systems that are implemented in practice settings, in most instances, cannot be evaluated with traditional experimental methods [1,2].

Moehr [3] discusses some of the problems encountered in evaluating medical informatics applications. First, the definition of the system is ambiguous. The evaluation usually involves not only the information system but also its impact on the organizational environment in which it is implemented. In fact, Moehr suggests that, in evaluating medical information systems, we are evaluating a dynamic process of adaptation of a new system and its environment rather than a technical system. Second, measurement methods and instruments for data collection and parameter estimation frequently need to be specifically developed for the evaluation. Third, the use of a randomized controlled design for the evaluation requires a level of specificity and objectivity that may vitiate many important objectives of the evaluation. Moreover, conventional evaluation methods frequently inadequately describe the dynamic properties of the system under investigation.

One approach to evaluation that provides flexibility is computer simulation. System simulation is defined ". . . as the technique of solving problems by following changes over time of a dynamic model of a system" [4]. The model that is used in the simulation is an abstraction of the real system that is being evaluated. Models are used to represent the system because they can be manipulated without disrupting the real healthcare setting. Once validated, they yield accurate estimates of the behavior of the real system. In many instances, the medical informatics system under study is too complex to be evaluated with traditional analytical techniques. Using simulation, an investigator can express ideas about the structure of a complex system and its processes in a precise way. Simulation can be used even in situations where the behavior of the system can be observed but the exact processes that generate the observed behavior are not fully understood. A computer model that represents important aspects of the system can be constructed. By running the model, we can simulate the dynamic behavior of the system over time. The effects of variations in system inputs, different initial conditions, and changes in the structure of the system can be observed and compared.

The Modeling Process

Systems Analysis

The development of a computer simulation model begins with the identification of the elements of the system and the functional relationships among the elements. A systems diagram is constructed to depict subsystems and components and relationships among them. The diagram should also show critical inputs and outputs; parameters of the system; any accumulations and exchanges or flows of resources, personnel, and information; and system performance measures. Relationships may be specified analytically, numerically, graphically, or logically. They also may vary over time.

Frequently applications of information technology that are to be evaluated are multifaceted. Subsystems and components are interrelated in complex ways and may be difficult to completely understand. Model development requires the investigator to abstract the important features of the system that generate the underlying processes. This requires familiarity with the system that is being evaluated and its expected performance.

Data Collection

Qualitative and quantitative information are required in order to adequately represent the system. Qualitative research methods are useful in defining the system under investigation. Quantitative data are necessary in order to estimate system parameters such as arrival and service distributions, conversion and processing rates, error rates, and resource levels. Data may be obtained from system logs and files, interviews, expert judgment, questionnaires, work sampling, and so on. Data may be cross-sectional and/or time series.

Model Formulation

In general, there are two types of simulation models, discrete-event and continuous. Swain [5] reviews 46 simulation software packages and provides a directory of vendors. The first two examples described in the next section are discrete-event models. The third example uses a continuous simulation model to describe the drug ordering and delivery system in a hospital.

Discrete-event models are made up of components or elements each of which perform a specific function [6]. The characteristic behavior of each element in the model is designed to be similar to the real behavior of the unit or operation that it represents in the real world. Systems are conceptualized as a network of connected components. Items flow through the network from one component to the next. Each component performs a function before the item can move on to the next component. Arrival rates, processing times and other characteristics of the process being modeled usually are random and follow a probability distribution. Each component has a finite capacity and may require resources to process an item. As a result, items may be held in a queue before being processed. Each input event to the system is processed as a discrete transaction.

For discrete-event models, the primary objective is to study the behavior of the system and to determine its capacity, the average time it takes to process items, to identify rate-limiting components, and to estimate costs. Simulation involves keeping track of where each item is in the process at any given time, moving items from component to component or from a queue to a component, and timing the process that occurs at each component. The results of a simulation are a set of statistics that describe the behavior of the simulated system over a given time period. A simulation run where a number of discrete inputs to the system are processed over time represents a sampling experiment.

Continuous simulation models are used when the system under investigation consists of a continuous flow of information, material, resources, or individuals. The system under investigation is characterized in terms of state variables and control variables [7]. State variables indicate the status of important characteristics of the system at each point in time. These variables include people, other resources, information, and so on. An example of a state variable is the cumulative number of medication orders that have been written on a hospital unit at any time during the simulation. Control variables are rates of change and update the value of state variables in each time period. An example of a control variable is the number of new medication orders written per time period. Components of the system interact with each other and may involve positive and negative feedback processes. Since many of these relationships are nonlinear, the system may exhibit complex, dynamic behavior over time.

The mathematical model that underlies the simulation usually consists of a set of differential or finite difference equations. Numerical solutions of the equations that make up the model allow investigators to construct and test models that cannot be solved analytically [8].

Model Validation

Once an initial model is constructed it should be validated to ensure that it adequately represents the system and underlying processes under investigation. One useful test of the model is to choose a model state variable with a known pattern of variation over some time period. The model is then run to see if it accurately generates the reference behavior. If the simulated behavior and the observed behavior of the system correspond well, it can be concluded that the computer model reasonably represents the system. If not, revisions are made until a valid model is developed [9,10]. The behavior of the model when it is manipulated frequently provides a much better understanding of the system. This process has been termed postulational modeling [11].

Sensitivity analyses also should be performed on the model. Frequently, the behavior of important outcome variables is relatively insensitive to large changes in many of the model's parameters. However, a few model parameters may be sensitive. A change in the value of these parameters may result in major changes in the behavior pattern exhibited by the system. It is not only important to accurately estimate these parameters but they may represent important means to change the performance of the overall system.

Advantages of Simulation

Simulation provides a powerful methodology that can be used to evaluate medical informatics applications. Modifications to the system or process improvements can be tested. Once a model is created, investigators can experiment with it by making changes and observing the effects of these changes on the system's behavior. Also, once the model is validated, it can be used to predict the system's future behavior. In this way, the investigator can realize many of the benefits of system experimentation without disrupting the practice setting in which the system is implemented. Moreover, the modeling process frequently raises important additional questions about the system and its behavior.

Applications

A Wide-Area Healthcare Network

A number of health informatics network projects utilize existing telephone networks. The University of Nebraska Medical Center provides an electronic mail service and access to databases for rural physicians [12]. Another project that was developed in conjunction with the University of Virginia Medical Center supports the exchange of electronic insurance claims data [13]. In Europe, the Advanced Informatics in Medicine (AIM) program is designed to support a wide range of health informatics applications [14].

This research project was undertaken to evaluate the behavior and cost of a wide-area healthcare network [15]. The system was a prototype message store and forward telephone system. Simulation studies were performed on two network topologies, namely, star and mesh. A discrete-event simulation model was constructed to represent a telecommunication network that would link general practitioners, specialists, municipal and regional hospitals, and private medical laboratories in the Canadian province of Saskatchewan. The model was used to simulate the distribution of laboratory test results by private, provincial, and hospital laboratories.

Two different network topologies, star and mesh, were analyzed. The networks consisted of eight subnetworks, one in each region of the province. Figures 9.1 and 9.2 depict the two types of networks. Each subnetwork has a hub or gateway that stores and forwards messages to the nodes. In the star network, a message sent from a node in a subnetwork to another node is stored at the hub until its destination node picks it up. If the destination node is in another subnetwork, the message must pass through another hub before it is delivered to a node. In the mesh network topology unlike the star topology, messages can be transmitted directly between two nodes in the same subnetwork without first passing through the hub. Messages transmitted from and to nodes in different subnetworks must pass through both hubs as previously described.

The simulation software used to model the two networks was written for an IBM compatible PC in Visual C++. Model parameters were based on measurements taken from a prototype network and a survey of two medical clinics. Communication among the gateways and between gateways and their nodes for a period of 24 h were simulated. Table 9.1 shows the summary results of the simulation. Only messages containing data were simulated.

The two networks differ in performance when communication among the eight gateways or hubs is compared. Over three times as many connections are originated in the star network as in the mesh network. Gateway utilization of the mesh model is two-thirds of the utilization of the star model. Mean message transmission time in the mesh network, however, is greater. Four times as many messages are transmitted by the gateways to the nodes in the star topology as compared to the mesh topology. This reflects the fact that in the star network, messages between nodes in the same subnetwork need to be transmitted by the gateway.

The end-to-end network performance characteristics of the two topologies also differ. In the star network, only two-thirds as many connections

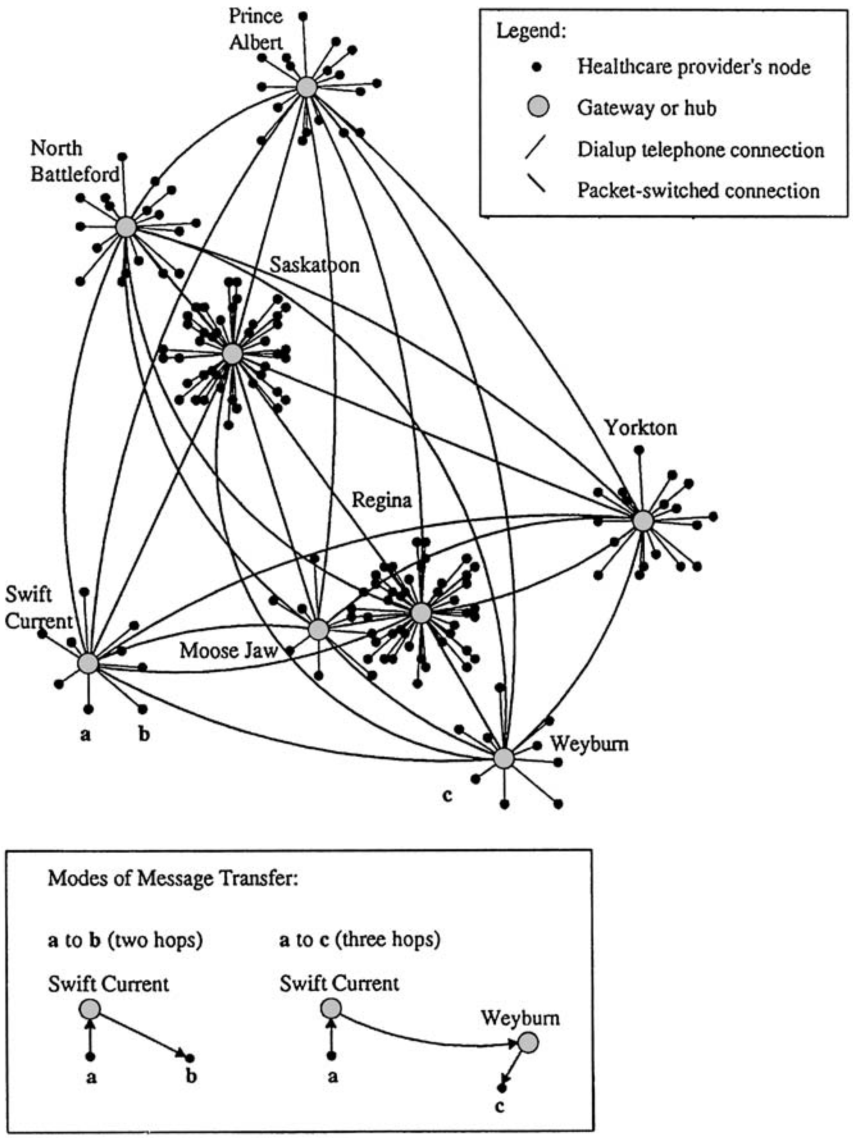

Figure 9.1. A schematic of a telecommunication network (star topology). (Reprinted with permission from JG McDaniel, Discrete-event simulation of a wide-area healthcare network. *JAMIA* 2(4) 1995, 220–237.)

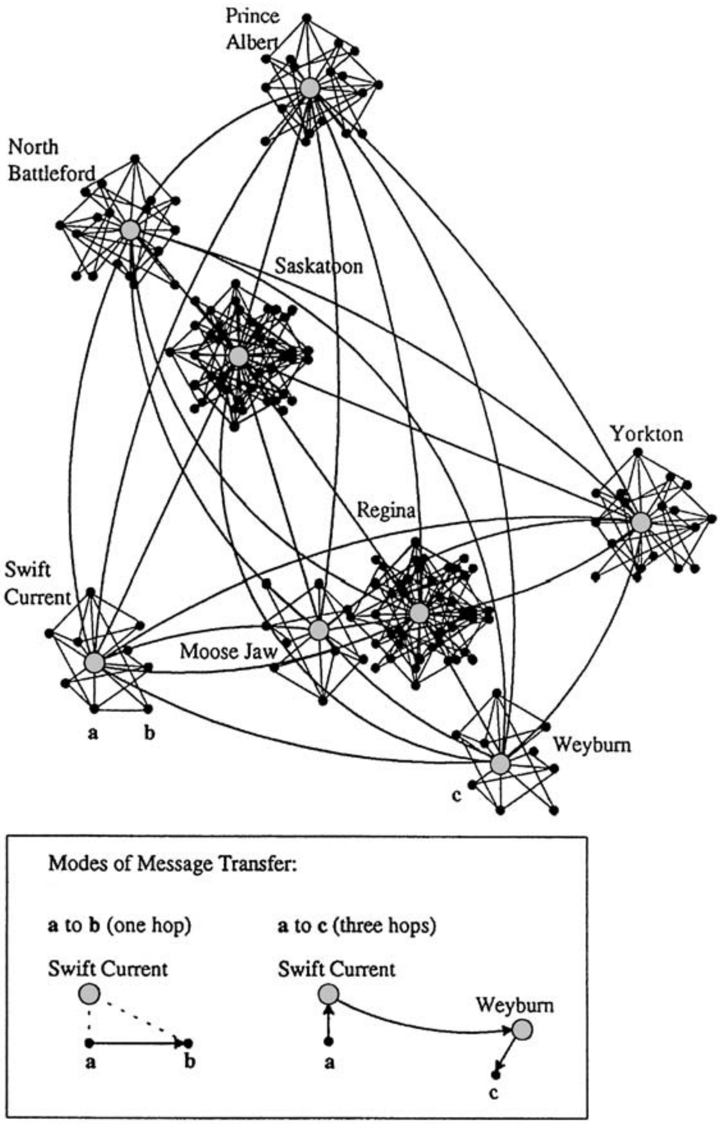

FIGURE 9.2. A schematic of a telecommunication network (mesh topology). (Reprinted with permission from JG McDaniel, Discrete-event simulation of a wide-area healthcare network. *JAMIA* 2(4) 1995, 220–237.)

are originated as compared to the mesh model. This reflects the fact that, in the star topology, nodes within the same subnetwork cannot connect directly to one another. The total connection time is 1.5 times greater in the star network because all messages must pass through subnetwork gateways. The mean message transmission time for the two network topologies is comparable.

Table 9.1. Performance statistics for the star and mesh networks.

Statistic	Star	Mesh
Number of connections originated between gateways	10,000	3,000
Percentage gateway port utlization	12	8
Mean data message transmission time(s)	8	10
Number of data messages transmitted by gateways to their respective nodes	80,000	20,000
Number of end-to-end connections between nodes	40,000	40,000
Total connection time at point of origin (h)	300	200
Mean end-to-end message transfer time (h)	1.24	1.23

Table 9.2 summarizes the telecommunication costs for the two network topologies. The estimated total monthly costs for the star network is $58,100 or about 40% of the cost of the mesh topology. This differential is also reflected in the costs per node for the star and mesh network topologies of $37 and $91, respectively. The higher costs of the mesh model are due to the fact that physicians are provided with dedicated telephone access under this network configuration.

The results of the simulation indicate that the telecommunication system in Saskatchewan could be operated for <$100 per node per month. It is estimated that the cost of the star network is about 40% of the cost of the mesh network. A typical message would cost between $0.03 and $0.08. Adding hospital discharge summaries and consultation reports to the messages transmitted by the system would double the data volume and increase the telecommunication costs by 60%. The simulation indicates that this would increase the mean end-to-end transfer time by less than 50%.

Physician Order Entry

There is evidence that direct order entry by physicians into computer-based medical information systems can improve the quality of care and reduce costs. Major advantages of physician order entry include process improvement, clinical decision support, reduction of errors, and improved communication within the healthcare setting [16]. Achieving physician order entry is difficult, however. Both social and logistical barriers to implementation exist [17].

The objective of this study was to develop a computer simulation model to represent the process through which medical orders are entered into a

Table 9.2. Telecommunication costs for the star and mesh networks.

Costs	Star	Mesh
Total monthly costs	$58,100	$145,100
Costs per node	$37	$91

hospital information system (HIS) [18]. The model was used to estimate the effects of increasing the percentage of medical orders that physicians enter directly into the HIS.

The study was performed in a large private teaching hospital. The hospital had implemented the TDS HC 4000 hospital information system. During hospitalization, all patient data are entered into the system creating an electronic medical record. Nursing units are equipped with between three to seven computer terminals linked to the HIS. Physicians, nurses, unit secretaries, and other authorized personnel can enter and retrieve patient information using these terminals.

In order to study use of the HIS, data were collected from two sources. Four weeks of patient data were extracted from the information system files. Also, a time and motion study was performed on order entry into the HIS. INSIGHT, a general-purpose discrete-event simulation language, was used to construct a simulation model of the order entry process. The model is shown in Figure 9.3.

At Stage A, a set of medical orders is created for entry into the HIS. Order entry arrival times are generated by a probability distribution. Attributes are assigned to the orders at Stage B. At Stage C, the physician can directly enter orders at a computer terminal, or orders can be written or verbally communicated. If the physician does not enter his or her orders into the HIS at Stage D, orders are entered by a unit secretary. Next, the orders are printed and filed on the nursing unit as well as in the appropriate ancillary services at Stage E. An RN on the nursing unit verifies the orders at Stage F by comparing the written or verbal orders to printed orders. If errors are detected, they are corrected and reentered in the HIS. Otherwise the patient's chart containing the medical orders is stored in the chart rack and the orders are executed at Stage G.

The model was first used to simulate the initial conditions on a hospital unit. Resources included 6 physicians, 3 physician assistants, 2 RNs, 2 unit secretaries, 7 computer terminals, and 2 printers. A total of 227 sets of orders were simulated over a 16-hours period. The initial simulation assumed that 89% of orders were written and that physicians only entered eight percent of the orders. It was also assumed that unit secretaries, physicians, and physician assistants used personal order sets to enter 29%, 50%, and 13% of the medical orders, respectively. Personal order sets are medical orders that are designed for a specific physician or group of physicians and stored on the HIS for use in entering orders. The alternative is to use generic order entry screens provided by the vendor. A second simulation assumed the same resources were available on a hospital unit. However, it was assumed that use of personal order sets for order entry by unit secretaries, physicians, and physician assistants increased to 50%, 75%, and 50%, respectively. Table 9.3 shows the results of the two simulations.

Under the initial conditions, it took 36.9 min on average to process a set of medical orders. Most of this time, 33.6 min, was due to the unavailability

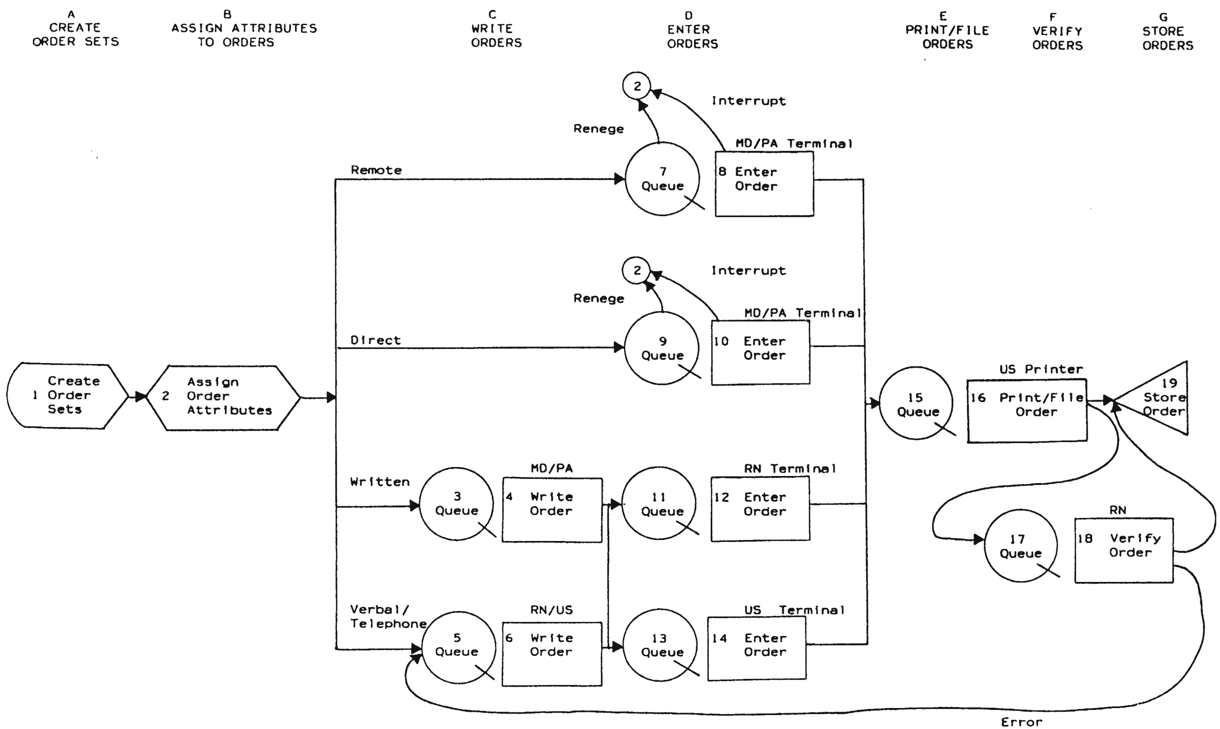

FIGURE 9.3. Computer simulation model of physician order entry into a hospital information system. (Reprinted with permission from JG Anderson, SJ Jay, SJ Clevenger, DR Kassing, J Perry and M Anderson, Physician utilization of a hospital information system: a computer simulation model. In: *Proceedings of the 12th Annual Symposium on Computer Applications in Medical Care* (1988), pp. 858–861.)

Table 9.3. Results of the computer simulation experiments.

Outcome variables	Initial conditions	Experimental conditions
Average time to implement order sets	36.9 min	33.2 min
Average order entry time		
MD	4.6 min	2.9 min
PA	2.6 min	1.6 min
US	1.8 min	1.4 min
Waiting time		
Order entry	12.4 min	9.9 min
Filing orders	3.9 min	3.3 min
Verification	17.3 min	17.3 min
Total	33.6 min	30.5 min
% Time involved with HIS		
MD	4.1%	3.5%
PA	0.5%	0.4%
US	21.9%	17.7%
RN	3.0%	3.0%
Terminal	9.8%	6.9%
Error rates (per 1000 orders)	40.9	33.0

of personnel or a computer terminal. Unit secretaries spent 21.9% of their time processing medical orders. The overall error rate in processing medical orders was estimated to be 40.9 errors per 1000 orders.

When personal order sets are utilized to a greater extent and physicians enter more of their own orders into the HIS, the average time to process orders is only reduced to 33.2 min on average. One reason for this small decrease in processing time is that the waiting time required for RNs to verify the orders remains the same, 17.3 min on average. This step in the process appears to be critical in reducing the time it takes to process medical orders. A significant effect of direct physician order entry and the use of personal order sets is a decrease in the number of errors made in processing medical orders. The model estimates almost a 20% decrease in errors.

This study demonstrates how computer simulation can be used to evaluate a critical process such as order entry into a hospital information system. The model can be used to identify critical steps in the process, such as the lack of sufficient personnel to verify medical orders. Simulation can also be used to explore the effects of changes in the process such as increasing direct physician order entry and the use of personal order sets. In the present example, the simulation suggests that implementation of these changes in the process would significantly reduce errors in order entry.

Prevention of Adverse Drug Events

It is estimated that adverse drug events (ADEs) occur in hospitals at the rate of 6.5 events per 100 hospital admissions [19,20]. The estimated extra length of hospital stay resulting from ADEs is 1.74 days which adds an additional $2012 to the cost of hospitalization on average [21]. The increasing availability of electronic medical record systems makes it possible to detect errors and to prevent ADEs. This study developed a computer simulation model to estimate the effects of various medical informatics applications designed to detect and prevent medical errors that result in ADEs [22].

The study was performed in the private teaching hospital described earlier. Ninety-one percent of medication orders were written by physicians and entered into the hospital information system by unit secretaries. In order to collect data on medication order errors, hospital pharmacists verified every medication order written on two medical-surgical units during the day and evening shifts for a 12-week period. A total of 6966 orders were reviewed for this study. Errors that were detected were classified by the stage of the order and by its severity. In general, physicians made 14% of the errors in writing prescriptions; 83% of the errors were made during transcription and entry into the HIS. The other 3% of errors were made in dispensing and administering medications on the units. Twenty-six percent of the errors could have resulted in serious toxic reactions or inadequate treatment resulting in ADEs if not detected.

A computer simulation model was constructed to model the drug ordering and delivery system using STELLA, a continuous simulation software package [7]. The model is shown in Figure 9.4. The simulation assumes that, on average, 4060 medication orders are written on 14 hospital medical-surgical units each week. Ambulatory clinics and the emergency room were excluded from the simulation. In the baseline simulation, the majority of orders are entered into the HIS by unit secretaries. Medications are dispensed in the central pharmacy and delivered to the nursing units where they are administered by RNs.

The model is used to simulate interventions that have been demonstrated in previous studies to decrease medication error rates. In the first intervention, the computer-based information system provides dosing information and parameters about drugs at the time orders are written. It is assumed that 50% of the physicians would use the system to obtain this information. The second intervention assumes that 50% of the medication orders are directly entered into the information system by physicians thus reducing transcription errors. The third and fourth interventions involve the implementation of a unit dosing system in the pharmacy and an automated medication dispensing system, respectively. The final intervention that was simulated assumes that system-wide changes are introduced that include the provision of information concerning each drug at the time orders are entered, direct order entry by physicians, and predictions of potential adverse drug events based on clinical data. Table 9.4 shows the results of the simulations.

The baseline simulation predicted over 8000 medication errors would be made over the course of 12 months. These errors would result in 2115 ADEs and incur 4654 additional days of hospitalization at a cost of over 5.5 million dollars. The model predicts that each of the individual interventions

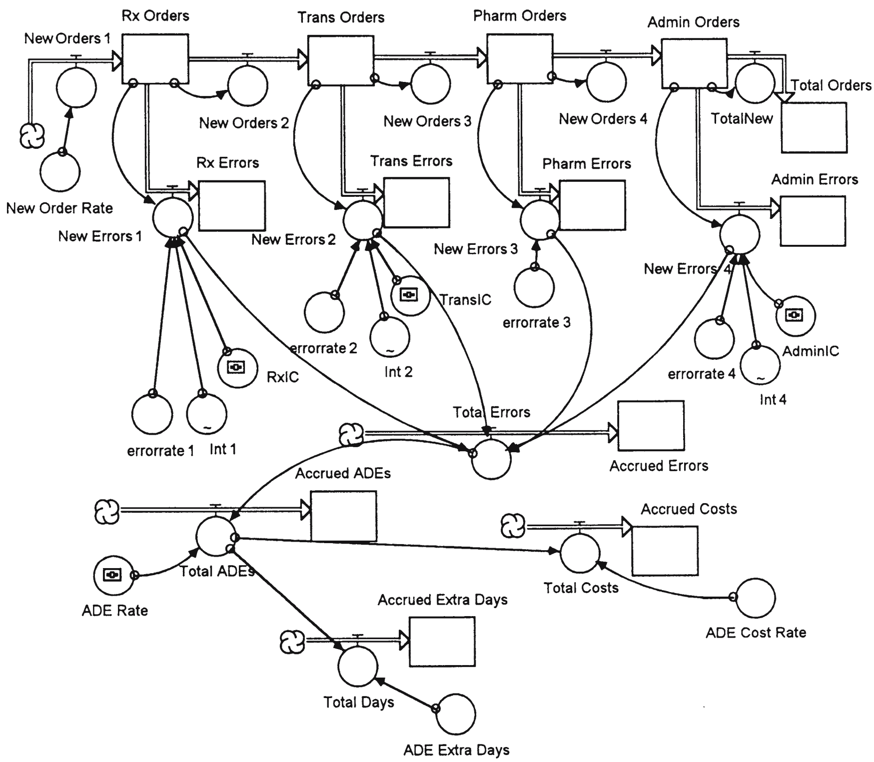

FIGURE 9.4. Computer simulation model of the drug ordering and delivery system of a hospital. (Reprinted with permission from JG Anderson, SJ Jay, M Anderson and TJ Hunt. Evaluating the potential effectiveness of using computerized information systems to prevent adverse drug events, in: *Proceedings of the 1997 AMIA Annual Fall Symposium* (1997), pp. 228–232.)

could reduce medication errors and resulting adverse drug events from 5% to 13%. However, implementation of all three applications could reduce ADEs by over 26%. This would have a substantial effect on excess hospital days and the resulting costs. The model estimates that additional hospital days related to ADEs could be reduced by 1226, saving the hospital $1.4 million in related costs annually.

TABLE 9.4. Estimated medication errors, adverse drug events, and associated extra costs and days of hospitalization.

Run	Orders	Medication errors	ADEs	Hospital days	Cost
Base line	195,392	8,136	2,115	4,654	5,489,752
Intervention 1	195,286	7,714	2,005	4,412	5,205,135
Intervention 2	195,245	7,099	1,845	4,061	4,790,148
Intervention 3	195,288	7,609	1,978	4,352	5,133,856
Intervention 4	195,196	5,993	1,558	3,428	4,044,135

The results of this study demonstrate the importance of viewing interventions designed to detect and prevent adverse drug events from a systems perspective. Errors occur at every stage of the drug ordering and delivery system. This study suggests that system-wide changes in the process are required to significantly reduce ADEs in hospitals. Medical informatics applications that focus solely on a single stage of the process may have a limited impact on the overall medication error and ADE rates.

Discussion

This chapter illustrates how computer simulation can be used to model and evaluate the performance of medical informatics applications. Three examples were discussed in detail. They include the implementation of a telecommunication system, direct physician order entry into a hospital information system, and the use of a hospital information system to detect and prevent medication errors that lead to ADEs. Two of the models used discrete-event simulation, while one used continuous simulation software.

The first example illustrates how simulation can be used before an information system is installed to evaluate the costs and performance of alternative system configurations. The second and third examples indicate how simulation can be used to explore potential improvements to an existing information system that might result in significant cost and error reductions. In all three instances, simulation provides a useful methodology where traditional evaluation methodologies are restricted or costly to employ.

The new generation of simulation software that incorporates graphical interfaces greatly facilitates exploratory studies of complex systems by freeing the investigator from dealing with complex mathematical expressions and programming languages. These computer models, through their use of graphics, provide a powerful means of communicating and exploring model assumptions, structure, and the resulting dynamic behavior of a system. This approach is applicable to a wide variety of medical informatics applications and can be used to better understand their complex dynamic behavior.

Summary

Computer simulation can be used to evaluate complex information systems in situations where traditional methodologies are difficult or too costly to employ. The modeling process is described followed by three examples where computer simulation has been utilized in planning for a wide-area healthcare network and in the use of a hospital information system to reduce costs and errors in order entry.

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