Original Article

Impact of Pharmacy Automation on Patient Waiting Time: An Application of Computer Simulation

Woan Shin Tan,[1] *MSocSc*, Siang Li Chua,[1] *MTech(KE)*, Keng Woh Yong,[2] *BPharm(Hons), MSc*, Tuck Seng Wu,[2] *BPharm(Hons), MHSM*

Abstract

Introduction: This paper aims to illustrate the use of computer simulation in evaluating the impact of a prototype automated dispensing system on waiting time in an outpatient pharmacy and its potential as a routine tool in pharmacy management. **Materials and Methods**: A discrete event simulation model was developed to investigate the impact of a prototype automated dispensing system on operational efficiency and service standards in an outpatient pharmacy. **Results**: The simulation results suggest that automating the prescription-filing function using a prototype that picks and packs at 20 seconds per item will not assist the pharmacy in achieving the waiting time target of 30 minutes for all patients. Regardless of the state of automation, to meet the waiting time target, 2 additional pharmacists are needed to overcome the process bottleneck at the point of medication dispense. However, if the automated dispensing is the preferred option, the speed of the system needs to be twice as fast as the current configuration to facilitate the reduction of the 95th percentile patient waiting time to below 30 minutes. The faster processing speed will concomitantly allow the pharmacy to reduce the number of pharmacy technicians from 11 to 8. **Conclusion**: Simulation was found to be a useful and low cost method that allows an otherwise expensive and resource intensive evaluation of new work processes and technology to be completed within a short time.

Ann Acad Med Singapore 2009;38:501-7

Key words: Automation, Dispensing, Manpower, Outpatient Pharmacy, Simulation modelling, Waiting time

Introduction

The growth in the fields of healthcare, pharmaceuticals, life sciences and research in Singapore has increased the demand for and the scope of work of pharmacists. Despite the increase in the number of practicing pharmacists from 770 in 1997 to 1349 in 2007, Singapore still has a comparatively low density of pharmacy personnel of 3 per 10,000 population. In the United Kingdom, there are 5 for every 10,000 population whilst it ranges from 9 to 19 for the United States and Japan.[1] A survey of patients in Singapore[2] showed that besides prescription accuracy and affordability of medicine, patients expressed preference for waiting time to be less than 30 minutes. As determined from the administrative data of an outpatient pharmacy in Singapore, only about 27% of the patients were served within this target time.

To deal with the continued shortage of pharmacists and rising expectations from patients on service standards,

automation is being explored as a means to improve operational efficiency. As mechanisation replaces many repetitive and labour-intensive tasks currently undertaken by pharmacy personnel, it is purported to increase staff productivity and free pharmacists to practice pharmaceutical care. Reduction in filling errors and pharmacy waiting times[3-4] are also keenly expected outcomes. While the effects of automation on inventory control, billing, workload, potential medication errors[5] and prescription filling time have been evaluated in various studies,[6-8] the impact on patients waiting time for medication has not been adequately studied.

Implementing a new technology is costly and often requires substantial re-engineering of the workflow. A useful alternative to learning-by-doing or experimentation[9] is to use computer simulation to provide insights into complex systems and to predict the impact of policy changes on outcomes. Such models take the form of a set

[1] Health Services and Outcomes Research, National Healthcare Group, Singapore
[2] Department of Pharmacy, National University Hospital, Singapore
Address for Correspondence: Miss Tan Woan Shin, 6 Commonwealth Lane, #04-01/02 GMTI Building, Singapore 149547.
Email: woan_shin_tan@nhg.com.sg

of assumptions concerning the operation of the system, which are expressed in mathematical, logical relations between the components of interest. The behaviour of the system among the components is then replicated as it would occur in the real world with the use of a computer.

In clinical systems, discrete event simulation modelling is appropriate as it is able to deal with detail complexity such as different patterns of arrival, staffing schedules, and complex patient routing and scheduling.[10] Simulation model is also able to incorporate the stochastic nature of processes and the random behaviour of their resources. Finally, simulation models can capture the behaviour of both human and technical resources in the system. Many applications of simulation modelling can be found in the health care setting; determining staffing needs,[11] allocating hospital beds,[10] examining disease progression and response to treatment,[12] assessing efficiency and profitability of health care facilities[13] but relatively few focused on pharmacy systems.[14-16]

This study aims to illustrate the potential of simulation modelling to inform evidence-based health systems policy and practice. Specifically, the impact of a prototype automated dispensing system on achieving the 95th percentile patient waiting time target of 30 minutes was examined using discrete event simulation modelling. Commercially available automated prescription dispensing systems can be grouped into: robotic, cabinet cell, and countertop,[8] and are capable of picking tablets, capsules and boxes. However, as blister strips formed up to 70% of the medications dispensed at the study site, they were found to be unsuitable. As no commercially available solutions met our dispensing requirements, a prototype system needs to be built. The robotic system explored by the pharmacy managers and evaluated in this study, consisted of 2 arms, which can be used for gripping the blister strips.

Materials and Methods

Study Setting

The study was carried out at a single outpatient pharmacy located within a tertiary hospital in Singapore. The pharmacy operates between 8.30 a.m. and 7.00 p.m. on weekdays and between 8.30 a.m. and 3.00 p.m. on Saturdays. At the time of the study, the outlet was staffed with up to 7 pharmacists and 11 pharmacy technicians who work 7½-hour-shifts on weekdays and alternate Saturdays.

Pre- and Post-Installation Workflow Description

The current workflow is represented in Figure 1. Prescriptions written by the physicians are printed and given to patients who then proceed to the pharmacy. At the pharmacy, the patient first hands the printed prescription
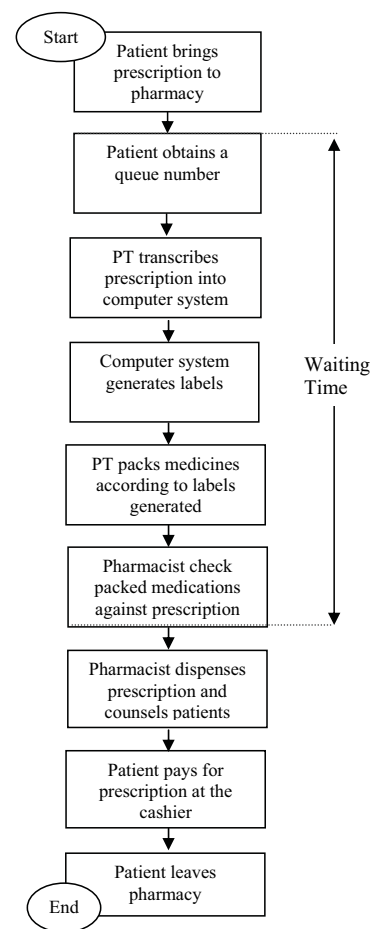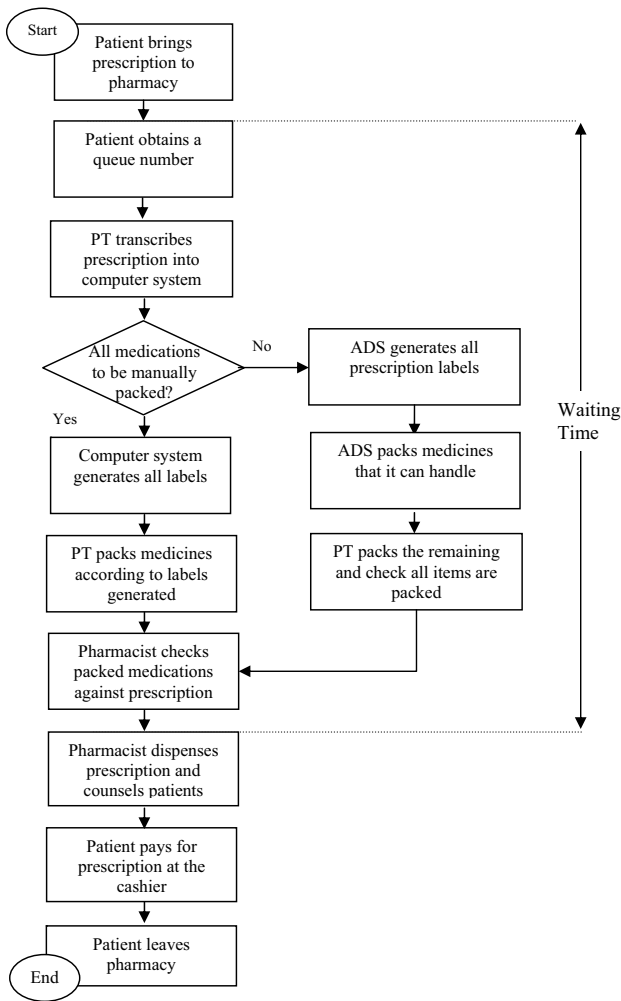

PT: Pharmacy Technician

Fig. 1. Process map of current workflow, pre-installation of automated dispensing system.

over to the counter staff in exchange for a queue ticket. The transcribing of orders, printing of prescription labels, and the packing of drugs are carried out by the pharmacy technicians and the packed drugs are checked against the prescriptions by the pharmacists. Lastly, the pharmacist counsels and educates the patient on the side effects, precautions to observe and the proper use of medicines.

A different workflow was mapped out by staff members of the pharmacy to incorporate the automated dispensing system (Fig. 2). As the prototype system only picks and packs blisters and foils, the remaining prescription items made up of loose tablets, liquid medication in bottles, cans or ampoules, gel, ointment and cream in tubes or jars, powder in sachets or packets, refrigerated items and controlled drugs, have to be packed manually. In this new workflow, an additional step in the process is required. The pharmacy technician will first need to sort out prescriptions with drug items that must be manually packed. For

PT: Pharmacy Technician; ADS: Automated Dispensing System

Fig. 2. Process map for workflow incorporating the automated dispensing system.

prescriptions containing drug items requiring both manual and machine packing, it will be channelled to the machine first with the unfinished prescription deposited in an out-tray to be completed by the pharmacy technician.

Discrete Event Simulation Model

A discrete event simulation model was constructed to estimate the impact of an automated dispensing device on patient waiting time. A stochastic model was used as many of the inputs are probabilistic. The final outcome of interest is patient waiting time, which is calculated as time from which the patient submits the prescription at the pharmacy to the time at which the patient is called to receive the medication. The Simul8 Standard software (2005, Simul8 Corporation, Boston, Massachusetts) was used.

Model Assumptions and Parameters

The on-screen appearance of the model with and without the automated dispensing system is shown in Figure 3. In the model, entities, events, and resources were used. The entities considered in the model include prescription, which represent the work items that flow through the simulation. "Transcribe", "Pack", "Check" and "Dispense" stand for work stations at which prescriptions are processed. "Rx Q", "Pack Q", "Check Q" and "Dispense Q" represent storage bins where a prescription has to wait until appropriate resources or work centres become available. Resources included "Pharmacy Technicians" and "Pharmacists" whereas "Arrival" and "Medicine Collected" represent the entry and exit points for entities. Other key events such as patient arrival and departure from the pharmacy, staff shift-changing and processing of prescriptions by pharmacy staff or by the automated dispensing device were incorporated. An explicit simulation clock keeps track of the passage of time with time units set in minutes. All prescriptions are processed in first-in-first-out (FIFO) basis. Non-dispensing duties such as stock replenishment were excluded from this study.

Although the outpatient pharmacy also operates on weekends, this study only considered weekdays as waiting time is not a problem on Saturdays due to a more manageable workload. The length of each model run is 1 simulated day. The simulation starts at 8:30 a.m. when patients will arrive at the pharmacy and ends at 7.30 p.m., half an hour after the pharmacy closes so as to cater for any unfinished jobs. Any unfinished jobs after 7.30 p.m. were discarded. The mean half-hourly patient arrival rate was obtained from an in-house data system for January 2006 and was used to compute the inter-arrival time. On average, patient arrival peaks at 11.00 a.m. to 11.30 a.m., and 3 p.m. to 3.30 p.m. and reaches a trough between 1.30 p.m. to 2.30 p.m. We assumed the distribution of the inter-arrival time to be non-homogeneous and exponential at half-hourly intervals. The
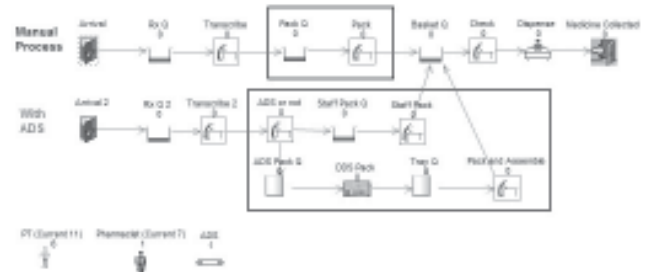
ADS: Automatic Dispensing System; Rx: Prescription; Q: Queue; PT: Pharmacy Technician

Fig. 3. On-screen appearance of models.

standard deviation of an exponential distribution is close to its mean. For each half-hourly interval, we found the ratio of the mean and standard deviation to be close to 1. In addition, we conducted a visual check of the inter-arrival time to ensure it approximates an exponential distribution.

The frequency distribution of the number of medications per prescription and the proportion of prescriptions to be packed either manually and/or by the automated system was extracted from an in-house pharmacy computer system. These values were defined at the start of the simulation. Only 12% of all prescriptions contain medications that can be fully picked and packed by the automated system. Manual processing was required for 47% while the remaining 41% required both manual and automated picking and packing. Each prescription entity is assigned a number of items that is randomly generated using the frequency distribution of the number of items in a prescription, and it follows the arrival distribution of patients.

The number of staff available changes throughout the 10½ pharmacy operating hours based on the pharmacy's daily staff schedule. Each staff worked a 7½-hour shift on weekdays. Half-hourly staff numbers were used to reflect labour inputs in the model.

Data describing the time taken by pharmacy technicians to complete transcribing prescriptions, and to pick and pack the drug items and by pharmacists to check the packed drug items against doctors' prescriptions and counsel patients at the time of dispense were derived from a self-reported time and motion study conducted in the same pharmacy over a one-week period. In total, 2210 records were collected by pharmacy staff over a one-week period. These service times fitted well to a triangular distribution. With the prototype system, low value-added tasks like picking, packing and labelling of medication for dispensing were automated. The system takes 20 seconds to pick 1 item and 20 seconds to pack 1 item. For each prescription, an additional 6 seconds is required for the discharge of the assembly tray. Parameters are summarised in Table 1.

Experimentation

We considered 4 different scenarios in the simulation: current workflow (Scenario 1), new workflow incorporating the automated dispensing system (Scenario 2) and 2 alternative scenarios. Since technical and human resources are substitutes in the prescription-filling process, we explored the independent impact of varying the number of pharmacy staff while holding all else constant (Scenario 3). The automation of the prescription-filling tasks will cover up to 53% of the pharmacy workload. Therefore, following

Table 1. All Parameters Used Within the Model

Parameter	Distributions and values used to define distributions	Source
Entities		
Prescription inter-arrival time	Exponential distribution for each half-hourly inter-arrival rate	In-house data system
Number of drug items per prescription	Empirical distribution. 33% (1 item); 19% (2 items); 11% (3 items); 37% (>3 items)	In-house data system
Prescriptions filled by automated dispensing system	No distribution. Full: 12%; Partial: 41%	In-house data system
Resources		
Number of pharmacists	Follows staff schedule. Maximum available = 7	Pharmacy manager
Number of pharmacy technicians	Follows staff schedule. Maximum available = 11	Pharmacy manager
Prescription processing time per prescription* (Minutes)		
Transcribe	Triangular. Min (0.1); Mode (0.5); Max (1.0)	Time study
Pick and Pack (Manual)†	Triangular. Min (0.5); Mode (1.0); Max (15.0)	Time study
Pick and Pack (Automated)	No distribution. 0.77	Pharmacy manager
Check	Triangular. Min (0.25); Mode (0.5); Max (1.0)	Time study
Dispense	Triangular. Min (1.0); Mode (2.0); Max (11.5)	Time study

Min: minimum; Max: maximum

* Transcribe: time taken by pharmacy technician to type out prescription details; Pick and Pack: time taken by pharmacy technician to obtain an empty prescription basket, paste the labels on the drug containers, and pick and pack the required drug items, or time taken by the automated dispensing system to pick and pack the required drug items and to discharge the assembly tray; Check: time taken by pharmacist to retrieve a filled prescription and to check the packed drugs against the prescription order; Dispense: time taken by pharmacist to call the queue number indicated on the paper prescription and to counsel the patient.

† The amount of time taken to manually pick and pack ranges between 30 seconds to 15 minutes depending on the number of items in the prescription.

a simplistic but intuitive deduction, the number of pharmacy technicians can be reduced proportionately. To explore this assumption, Scenario 4 will simulate the combination of technical and human resources needed to achieve the 30 minutes maximum waiting time target under the new workflow.

Model Verification and Validation

Model verification included close examination of the animation, step-by-step running of the model and following the logical path of a single entity through it, and double-checking of the model logic with the pharmacy staff.[17] To validate the baseline model, we ensured that the output volume and shares of prescriptions packed manually and/ or automatically were consistent with the input data. We validated the mean, median and maximum patient waiting time generated by the model against actual waiting time data extracted from the administrative system. The differences were found to be operationally insignificant (Table 2). As the minimum number of replications required to achieve the precision level of +/-10% is 29, 100 replications were conducted for each scenario.

Results

Table 2. Verification of Simulation Model

Patients' waiting time	Actual system data (min)	Simulated results (min)	Difference (%)
Mean	20.2	22.9	13.3
Median	21.0	21.6	2.7
95th percentile	36.7	42.6	16.1

%: percentage

The simulation results are summarised in Table 3. The results suggest the presence of a process bottleneck at the stage where pharmacists dispense prescription and counsel patients on their prescribed therapy in both Scenario 1 and Scenario 2. Other than this, the simulation also highlighted that given the policy of routing prescriptions that contain items to be both manually and machine packed to the automated dispensing system first, a process bottleneck will occur as prescriptions queue to be processed by the automated system in Scenario 2. Thus, the introduction of the automated dispensing system alone will not reduce the 95th percentile patient waiting time to below 30 minutes, as patients will continue to wait up to a maximum of 58.2 minutes.

Since the results are highly dependent on the number of pharmacists, sensitivity analyses were conducted. If we employ 2 additional pharmacists, the maximum patient waiting time can be lowered to 27 minutes in Scenario 3 without having to automate. Conversely, with automation, the speed of the system needs to be doubled concomitantly with the increase in the number of pharmacists to reduce the 95th percentile waiting time to below 30 minutes. However, with the faster processing speed, the pharmacy will be able to reduce the number of pharmacy technicians from 11 to 8 while holding waiting time for patients constant.

Discussion

Computer simulation modelling is a powerful tool that can support evidence-based health care policies and management. Many existing healthcare interventions are diffused before evidence of effectiveness can be established.[18] Since mistakes can be expensive and

Table 3. Patient Waiting Time and Process Queue Time (minutes)

	Scenario 1	Scenario 2	Scenario 3	Scenario 4
Number of PT, Pharmacist, ADS	11,7,0	11,7,1	11,9,0	8,9,1
Patient waiting time				
Mean	22.9	25.4	11.5	11.4
(95% CI)	(21.7 – 24.2)	(24.2 – 26.6)	(11.3 – 11.7)	(11.3 – 11.6)
Median	21.6	22.5	10.9	10.4
95th percentile	42.6	52.6	19.0	18.4
Mean process queue time				
Transcribe	0.4	0.1	0.4	0.7
Manual pick and pack	0.3	0.1	0.3	0.2
ADS pick and pack	-	7.0	-	0.4
Dispense	13.2	11.1	0.9	0.9

CI: confidence interval; ADS: Automated Dispensing System

disinvestment difficult, the use of a simulation model to test out new technology and workflow in a risk-free environment and to inform decisions will improve efficiency and sustainability of resources allocated. With the rapid development of software and computing and the wide application of the tool, computer simulation is likely to increasingly become routine and fundamental in the management of health care. The visual interactive features of many simulation packages also facilitate communication with health care administrators because model behaviour can be presented graphically for discussion.

While there is evidence in literature to suggest that the automation of the pharmacy dispensing function reduces prescription-filling time,[8] and dispensing errors,[19,20] the performance of a new technology can be context-dependent. Modelled to reflect specific environments, simulation models serve as a decision support tool that estimates the impact on the system by replicating dynamic changes of the system and capturing the effects of stochastic events and random behaviour of resources. In this study, we explored the impact of an automated dispensing system on the workflow and service standards in the outpatient pharmacy using a discrete event simulation model. In addition, we were able to conduct scenario analyses to assess the impact of various resource combinations on patient waiting time, which would otherwise not be feasible to experiment with in real life.

Contrary to the pre-simulation hypothesis held by pharmacy managers that automation will improve the processing speed and lower patient waiting time, the simulation results showed that the automation of the prescription-filling task alone will not bring about a reduction in the 95th percentile waiting time to below 30 minutes. Results from Scenario 1 and Scenario 2 further indicate the impact of the shortage of pharmacists on operations. It will be difficult to improve pharmacy turnaround time if this problem remains unresolved. However, if the pharmacy is able to employ two additional pharmacists, the waiting time target of 30 minutes can be achieved without the need to invest in a new automated dispensing system (Scenario 3).

In theory, the automated dispensing system has the potential to improve process time due to its zero variance in speed. Nonetheless, the feasibility of integrating a new technology into an existing workflow has significant impact on whether potential benefits can be reaped. As prescriptions containing items to be manually and/or machine packed have to be routed to the automated dispensing system first in the new workflow (Scenario 2), a bottleneck will result as prescriptions pile up while waiting to be processed. We can resolve this issue if prescriptions can be flexibly routed to either the pharmacy technician or the automated

dispensing system when the queue builds up but such a complex workflow is not feasible.

In order to lower the 95th percentile patient waiting time to 30 minutes, our simulation results in Scenario 4 suggests that we will need to increase the number of pharmacists to nine and to either double the speed of the automated dispensing system or to purchase 2 units of the machine. Additionally, we will be able to reduce the number of pharmacy technicians by 3 (27%), which is lower than the hypothetical proportionate reduction by 50%. Unless current financing constraints and the lack of pharmacy space for expansion can be overcome, these options are not feasible in the short term.

Our findings should be viewed in the context of our study's limitations. It is generally not feasible to build a simulation model that encapsulates all features of the real system. The models in this study have been kept constructively simple.[21] While they included all the essential elements of the real system, there are elements that were not incorporated. For example, process times could be longer due to additional staff work such as double-checking with the prescribing doctor in the case of anomalies in the prescription orders and we have assumed that prescriptions will be processed FIFO. However, in practice, pharmacies may prioritise electronic orders over manual orders. In addition, the prototype explored could only fill 12% of all prescriptions and partially fill another 41%. Expansion of the packing capability of the automated dispensing system to cover up a larger share of the prescriptions could offer different results.

The evaluation of the benefits from automation in this study was focused on lowering patient wait times or essentially, prescription turnaround time. Administrators may also be interested in comparing the costs, prescription turnaround time, and safety between the manual and automated packing options. However, to conduct such an assessment, data on dispensing error rates with and without automation will be required. Our literature search did not yield any good quality studies that can inform our estimate of this parameter. Future research should attempt to evaluate the impact of automation on patient safety.

Computer simulation allowed an otherwise expensive and resource intensive primary study to be completed within a short-time scale at a minimal cost. The study also highlighted simulation as a useful communication tool, which have facilitated pharmacy managers' understanding of the current and potential processes as well as avoided the risks of making insufficiently informed decisions. This highlights the usefulness of this methodology in aiding healthcare decision-making faced with making decisions under uncertainty.

Conclusion

Simulation is often met with scepticism and distrust by first-time users due to its highly technical nature but it is a powerful method for investigating policy changes in the health care setting where complex relationships between input variables and outcomes exist. It is also a cost effective tool that helps to inform hospital administrators and supports evaluation of new technologies and purchasing decisions.

REFERENCES

1. World Health Organisation. World Health Statistics 2008. Available at: http://www.who.int/whosis/whostat/2008/en/index.html. Accessed 7 April 2009.
2. Tam VHY, Lim MM. Patients' perceptions and expectations of out patient pharmacy services in a teaching hospital. Int J Pharm Prac 1997; 5:128-32.
3. Baker KN, Felkey BG, Flynn EA, Carper JL. White paper on automation in pharmacy. Consult Pharm 1998;13:256-93.
4. Fitzpatrick R, Cooke P, Southall C, Kauldhar K, Waters P. Evaluation of an automated dispensing system in a hospital pharmacy dispensary. Pharm J 2005; 274:763-5.
5. Kaushal R, Bates DW. Information technology and medication safety: what is the benefit? Qual Saf Health Care 2002;11:261-5.
6. Borel JM, Rascati KL. Effect of an automated, nursing unit-based drug-dispensing device on medication errors. Am J Health Syst Pharm 1995;52:1875-9.
7. Lee LW, Wellman GS, Birdwell SW, Sherrin TP. Use of an automated medication storage and distribution system. Am J Hosp Pharm 1992;49:851-5.
8. Lin AC, Huang YC, Punches G, Chen Y. Effects of a robotic prescription-filling system on pharmacy staff activities and prescription-filling time. Am J Health Syst Pharm 2007;64:1832-39.
9. Fone D, Hollinghurst S, Temple M, Round A, Lester N, Weightman A, et al. Systematic review of the use and value of computer simulation modelling in population health and health care delivery. J Public Health Med 2003;25:325-35.
10. Ramis F, Palma JL, Baesler FF. The Use of Simulation for Process Improvement at an Ambulatory Surgery Centre. In: Peter BA, Smith JS, Medeiros DJ, Rohrer MW, editors. Proceedings of the 2001 Winter Simulation Conference; 1401-04.
11. Kumar A, Shim SJ. Simulating staffing needs for surgical instrument distribution in hospitals. J Med Syst 2006;30:363-9.
12. Sanga S, Sinek JP, Frieboes HB, Ferrari M, Fruehauf JP, Cristini V. Mathematical modeling of cancer progression and response to chemotherapy. Expert Rev Cancer Ther 2006;6:1361-76.
13. Weng ML, Houshmand AA. Healthcare Simulation: A Case Study at a Local Clinic. In: Farrington PA, Nembhard HB, Sturrock DT, Evan GW, editors. Proceedings of the Winter Simulation Conference 1999:1577-84.
14. Lin AC, Jang R, Sedani D, Thomas S, Barker KN, Flynn EA. Re-engineering a pharmacy work system and layout to facilitate patient counselling. Am J Health Syst Pharm 1996;53:1558-64.
15. Dean B, van Ackere A, Gallivan S, Barber N. When should pharmacists visit their wards? An application of simulation to planning hospital pharmacy services. Health Care Manag Sci 1996;2:35-42.
16. Vemuri S. Simulated analysis of patient waiting time in an outpatient pharmacy. Am J Hosp Pharm 1984;41:1127-30.
17. Sargent, Robert G. Validation and Verification of Simulation Models. In: Ingalls RG, Rossetti MD, Smith JS, Peters BA, editors. Proceedings of the Winter Simulation Conference 2004:17-28.
18. Elshaug AG, Hiller JE, Moss JR. Exploring policy-makers' perspectives on disinvestment from ineffective healthcare practices. Int J Technol Assess Health Care 2008;24:1-9.
19. Carmenates J, Keith MR. Impact of automation on pharmacist interventions and medication errors in a correctional health care system. Am J Health Syst Pharm 2001;58:779-83.
20. Oswald S, Caldwell R. Dispensing error rate after implementation of an automated pharmacy carousel system. Am J Health Syst Pharm 2007;64:1427-31.
21. Salt JD. Simulation Should be Easy and Fun! In: G. W. Evans, M. Mollaghasemi, E.C. Russell, et al, editors. Proceedings of the Winter Simulation Conference 1993:1-5.