Quantitative Case Study: Use of Pharmacy Patient Information Systems to Improve Operational Efficiency

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Abstract

In recent years, many US hospitals embarked on "lean" projects to reduce waste. One advantage of the lean operational improvement methodology is that it relies on process observation by the workers, and requires relatively little data [1]. However, as more operational data becomes available, hospitals may be able to prospectively evaluate and implement redesigns resulting in even more significant waste reductions. We provide one example of such a re-design in this case of a data-driven waste reduction project in an in-hospital pharmacy. A relatively simple mathematical model of the medication prepared and delivered by the pharmacy is used to estimate the savings from several potential approaches (rescheduling the start of production, scheduling multiple batches, or reordering production) as well the impact of some information system enhancements. We find that relatively small process changes, if implemented nationally, have the potential to save tens of millions of dollars annually.

1. Introduction

There have been several calls for the application of best practices in the design and management of processes to healthcare provision [2-8]. More recently there have been forecasts of great efficiency gains to be realized from the application of the knowledge that can be gleaned from 'Big Data' [9]. There have been some notable successes [8, 10, 11] but there have also been several reports regarding the difficulty of applying best practices from the fields of operations management and information systems partially due to a lack of data to support rigorous analysis [1, 12, 13] and a lack of data standards that impedes the ability of systems to leverage the data that does exist [2, 14].

In-hospital pharmacies turn out to be one department that have been required by strict regulations to collect copious amounts of data about the preparation and administration of medication. While data availability and standardization is not perfect in-hospital pharmacies provide a platform for exploring the potential for applying what has been learned from improvement efforts in other industries.

Here we present a short case study of the authors' interactions with personnel working in the in-house pharmacy of an 830-bed university-based hospital in upstate New York. At the time the department was considering moving to the production of compounded sterile products (CSP) used in intravenous drips from one batch per day to multiple batches with the objective of reducing waste. At the same time the hospital was implementing lean initiatives in many departments. We explore the use of mathematical modeling as a way of gaining insight into the department's operation and how this fits into the wider hospital context.

Next we provide an overview of the CSP preparation process at the hospital. This is followed by introducing a mathematical model of this process which we use to show how the pharmacy could leverage the information captured by its information systems to reduce waste. We estimate the savings from (a) rescheduling the daily batch to minimize the impact of cancellations, (b) scheduling multiple batches, and (c) the rescheduling the orders within a batch. We conclude by discussing the role of modeling and potential for leveraging information captured within operational systems.

2. Work and Information Flow

Orders for medications are entered by healthcare providers into a Pharmacy Information System (PIS). The following information about each order is stored:

- Patient id
- Prescribing provider id
- Name and dose of the medication
- Medication administration start date
- Medication administration end date
- Medication administration frequency

Administration frequency specifies how often the medication is to be administered. Figure 1 shows the distribution of administrations frequencies over a single month. For the majority of medication orders

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the difference between the end date and start date is greater than 2 days.

The PIS translates administration frequency into dose administration times. A "continuous" order also gets translated into administration times based on the specified infusion rate.

As preparing and dispensing compounded sterile products one at a time would be inefficient, they are traditionally produced in batches. The primary cause of the CSP waste of concern to the pharmacy director is the cancellation (or change) of orders that have already been prepared, or that are in the process of being prepared as part of the batch[15].

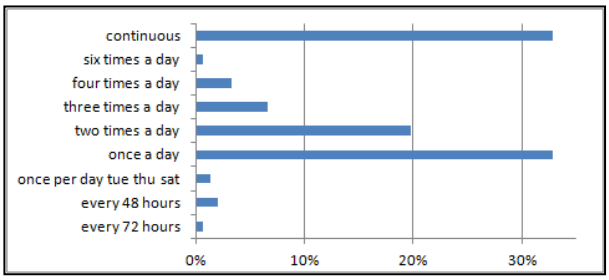

Figure 1. Distribution of Medication Administration Frequencies

In the hospital where our project was conducted, the original process configuration was such that at 6 am the PIS printed out labels for all order doses to be administered from 4pm that day until 3:59pm the following day. In addition to the information associated with the order, dose data consists of

- Scheduled dose administration time
- Delivery destination (i.e. nursing unit)
- Date and time the label is printed

The labels were distributed to pharmacy technicians who prepared CSPs to fulfill the orders. At about 2pm, after having been checked by a pharmacist, the prepared CSPs left the in-hospital pharmacy for batch delivery to the nursing units.

One of the consequences of batch preparation is medication waste: orders can be cancelled after a dose has already been prepared. The dispensed but not administered doses most often cannot be recycled: the logistics of collecting unneeded doses is complex and many of the CSPs have short expiration dates. Examining one month worth of data, we found that on average, 500 medication doses were prepared daily, and 20% of the prepared doses had scheduled administration times after the order cancellation time. Given the average cost of raw materials, the estimated annual waste was $365,000.

When an order was cancelled, a "cancellation" label was printed in the pharmacy. However, the production process utilizing labels made it difficult to stop production of a cancelled dose – a pharmacy employee would have to search among the 500 labels distributed among different technicians. Given tens of cancellations per day this was frequently not done, especially later in the day, as the dose was likely already prepared.

Pharmacy managers considered implementation of a new workflow system which required technicians to photograph different steps of CSP preparation, enhancing the audit trail and safety. One of the features of the new system is a virtual label queue, i.e. the physical labels are not printed until a technician is ready to prepare a particular dose. A virtual queue would allow easy cancellation of doses that have not yet been prepared. In evaluating the benefits and costs of the new system, pharmacy managers wanted to estimate the reduction in waste that could be achieved with the new workflow.

Most changes in pharmacy operations are evaluated empirically – with laborious data collection needed both pre- and post-implementation to assess their impact. Clearly, a reliance on the collection and counting of physical waste to measure improvements cannot provide insights in advance of the implementation of an intervention. Thus, the setting of realistic objectives for 'lean' or other change initiatives in such a context cannot be fact based. We created an analytical mathematical model to predict the number of wasted doses. Real world data on orders and cancellations extracted from the PIS were used to make the estimates.

In the next section we explain the development of our mathematical model for CSP inventory and demonstrate how it was used to estimate the reductions in waste that are possible.

3. Analytical Model for Calculating Waste

The tracking of prepared (or in preparation) CSP inventory at hour h (where $h = 1,2,\ldots,24$) is key to understanding the model. We use i_h^f to denote the total prepared CSP inventory under configuration f at time h. The units of i_h^f are hours of supply. To illustrate the concept we use an example based on the original operation of our pharmacy. Administration of a new batch started at 4 pm every day. Thus, the model assumes, for any particular order, a 24-hour supply of medication is in the nursing units at 4pm, a 23-hour supply at 5pm, a 22-hour supply at 6pm, etc.

The preparations of a new 24-hour batch started at 6 am, and took 8 hours to complete. To model this process we assume that an order is equally likely to be prepared between 6 and 7 am, between 7 and 8 am, and so on, up to 2 pm. The probability that the

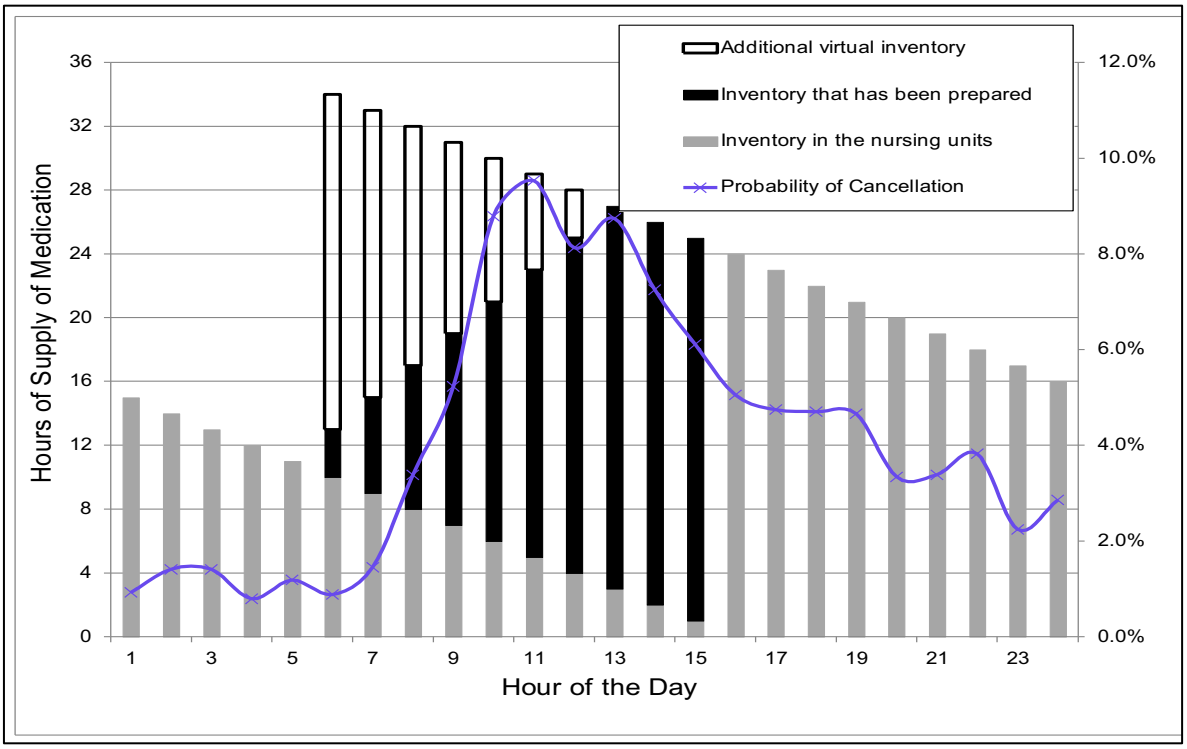

Figure 2. CSP Inventory and Orders Cancelled by Hour (%)

order is done by 2 pm is 100%, by 1 pm is 87.5% (i.e. 100% - 1/8), by noon is 75% (i.e. 87.5% - 1/8), etc. This model gives us the expected, or average, inventory of prepared medication for administration starting at 4 pm. By 2 pm the expected inventory is 100% of the 24-hour supply, by 1 pm it is 87.5%*24=21 hours' worth of supply, etc. Even though the medication may not have been prepared when a discontinue order arrived it was usually still prepared and thus wasted. To reflect that, we modeled inventory in preparation as a 24-hour supply from the time batch preparation begins. We termed the additional inventory as "virtual" inventory in preparation. The light gray columns in Figure 2 signify the inventory in the nursing units and the black columns correspond to the prepared CSP yet to be distributed to the nursing units. The columns without shading represent the virtual inventory i.e. the doses the pharmacy commits to preparing at the start of the batch as we assume that cancellations during the preparation time.

The expected waste resulting from the cancellation of a single order can be found as

$$w^f\left[\frac{hours\ of\ supply}{cancelled\ order}\right] = \sum_{h=1,..,24} c_h[\%] \cdot i_h^f, \quad (1)$$

where c_h is the probability of order cancellation in hour h. Using the data from our institution we found that 24.83 hours' worth of supply of medication inventory was expected to be wasted per single order cancellation. Of this 3.19 hours of supply was wasted due to virtual inventory. So changing the process to a virtual queue would result in estimated reduction of 3.19/24.83=12.85%, which given previous level of waste in our institution would imply that approximately 4700 fewer doses would be wasted annually, resulting in approximate annual savings of $47,000 in the cost of raw materials.

4. Additional Analysis Facilitated by Order Cancellation Time Stamps

The time of order cancellations was stored in the PIS (see Figure 3). This distribution is also superimposed (as a line plot) on the inventory model shown in Figure 2. This figure reveals that at times when order cancellations were most likely the expected level of CSP inventory was also high.

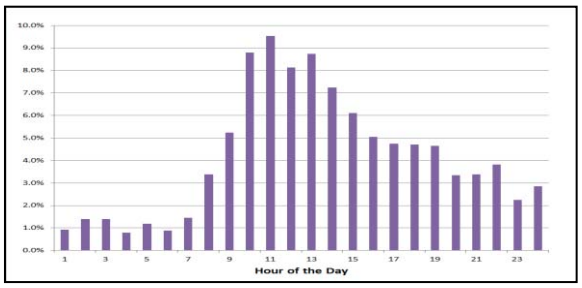

Figure 3. Probability Distribution of the Arrival Hour of Order Cancellation

We examined how shifting the start time of batch preparation, and subsequent batch delivery and administration would affect waste. For example, Figure 4 illustrates inventory levels when batch timing is shifted forward by 5 hours relative to the original schedule. Such a shift would result in an additional reduction in waste.

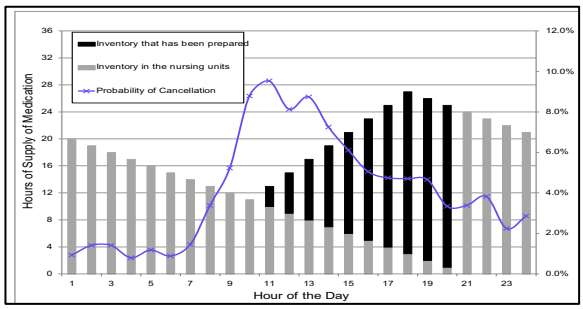

Figure 4. An Inventory Level Diagram That Assumes Batch Timing is Shifted by 5 Hours Relative to the Original Single Batch Schedule

Sensitivity analysis estimating the amount of waste (relative to the current start time, and post improved IT implementation) is shown in Figure 5. Shifting the process to later on in the day, could reduce waste by another 20%.

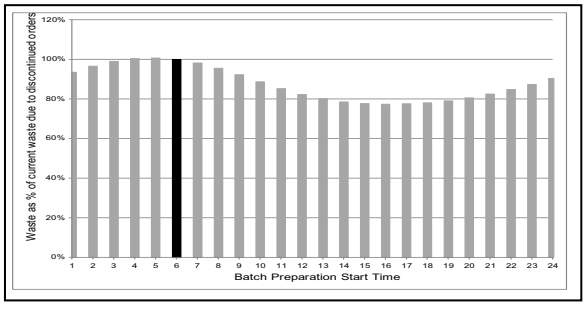

Figure 5. Changing Batch Preparation Start Time affects CSP waste

Recent articles describe efforts by in-hospital pharmacies to improve operations and to reduce CSP and other types of waste[15-18]. Some institutions have attempted to reduce CSP waste by increasing the number of daily production batches. Reports of such initiatives have prompted other pharmacy managers to ask what is the *optimal* number of batches for their institutions[19] as the answer has not been readily available. There is not a single optimal solution for every hospital of a certain size with a given mix of cases. Deciding on the number of batches must trade off the reduction in CSP waste associated with the preparation of fewer doses against the increase in employee hours needed for batch preparation and delivery. At least one pharmacy used a trial-and-error approach to find that waste reduction from going to six batches per day was more than offset by the additional labor required [15].

Multiple batch production can be analyzed in much the same way as single batch production. The following setup (illustrated in Figure 6) provides an example analysis of a configuration with two 12-hour batches. In the original configuration it took 8 hours to prepare 24 hours' worth of medication, so in a two-batch configuration we assume it takes 4 hours to prepare each batch. This assumption is dependent upon multiple batches not creating duplicate setup times for the clean room staff, if it does the savings will be smaller.

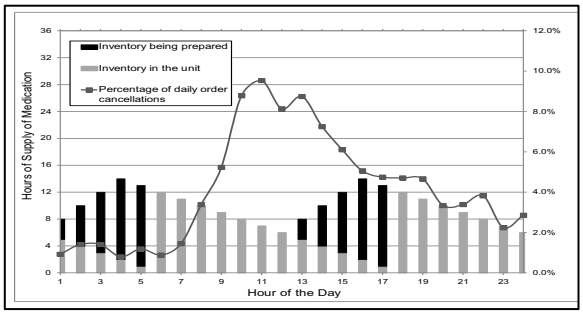

Figure 6. An Inventory Diagram for Time-Optimized 12-Hour Batches

Here we assume the timing of batches is optimized with respect to the distribution of order discontinuation times. The first batch prepares doses with administration start times from 6am until 5:59pm. This batch is prepared starting at 1am, leaves pharmacy at 5am, and is at the nursing units by 6am. The second batch is identical with preparation, delivery, and administration of medicine happening 12 hours later. Such a configuration results in 9.41 hours of wasted medication per discontinued order, which is a 56.5% decrease in waste relative to the original operational configuration, depicted in Figure 2. If the batches are not scheduled in a time-optimized way then the savings will be smaller.

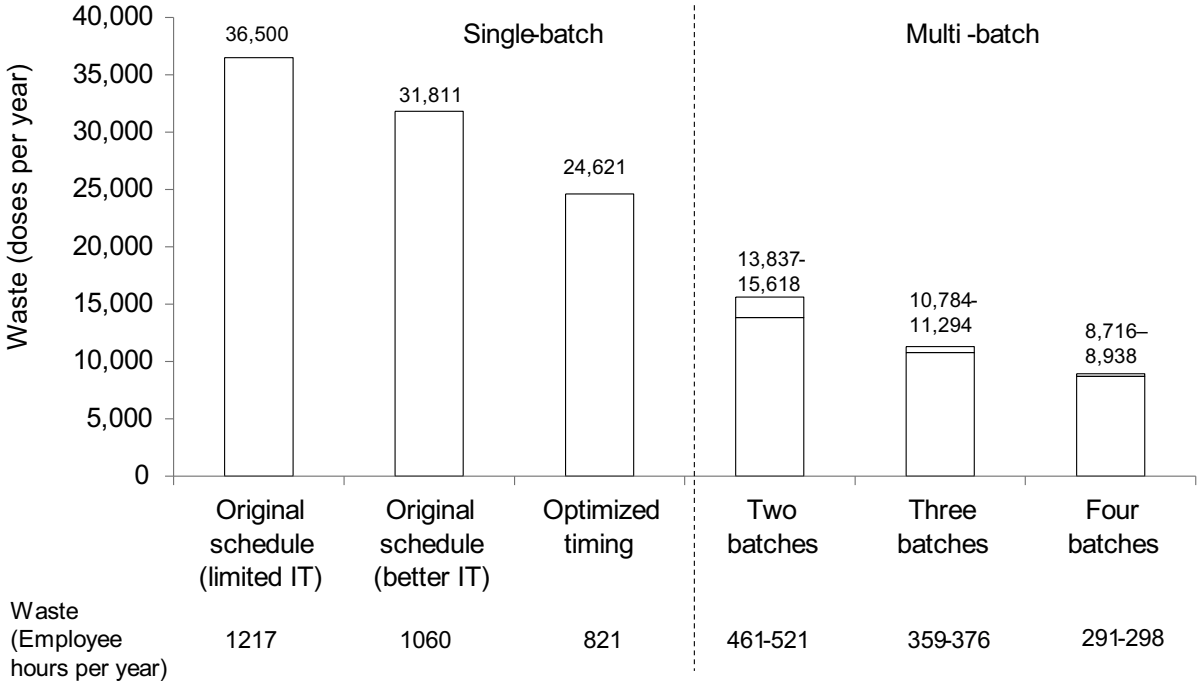

Figure 7. Compounded Sterile Product Waste under Range of Scenarios Discussed in the Text

Depending on the timing of the batches, going from a single batch to three 8-hour batches would provide a 64.5% to 66.1% reduction in waste. Using four 6-hour batches would result in a 71.9% to 72.6% reduction. Thus, as the number of batches increases, waste is further reduced, but at a decreasing rate. Also adjusting the timing of the batches to account for the pattern of discontinued orders becomes less and less important. Figure 7 charts the estimated waste reduction from different configurations. Pharmacy managers must be mindful of the fact that while adding batches reduces waste of employee time in preparation of doses, there is additional work involved with preparation and delivery of every extra batch. For example, transitioning from three 8-hour batches to four 6-hour batches would reduce waste by 2068 doses per year, therefore decreasing annual employee hours spent in dose preparation by 68.9. However assuming medication batches are delivered to 30 units and each delivery takes 5 minutes per unit, an additional 912.5 employee hours would be used in daily delivery of the additional batch. So, the net effect would be an increase of at least 843.6 in employee hours annually.

5. Estimating the Impact of Changing the Order of Medication Preparation

An alternative way to reduce waste costs without increasing the number of batches is by reducing the lead time for the preparation of more expensive drugs. This alternative requires a more involved calculation which we demonstrate next.

We assume that orders can be separated into two categories: expensive and inexpensive, with the expensive drugs comprising on average a quarter of all orders. The cost per dose of an inexpensive drug is $6.67, while the cost per dose of an expensive one is $20 (i.e., three times higher). The average cost is still $10 per dose. We consider the same overall production schedule as in Figure 2 the pharmacy starts preparing the batch at 6am and completes it 8 hours later at 2pm. It takes a further 2 hours to distribute the medication to the nursing units and its administration thus starts at 4pm. Expensive medications are a quarter of the overall volume, and we schedule these to be produced within the last two hours of batch preparation. The less expensive CSPs are prepared during the first 6 hours.

Following such a schedule (the inventory diagram is shown in Figure 8) we would reduce the amount of waste for expensive drugs to 16.8 hours of

supply, a 22.2% reduction relative to the original schedule. However, there will be more waste of the less expensive drugs, since there will be more hours when the inventory of the less expensive drugs is high. That means that on average, 23.2 hours of supply of the less expensive CSPs will be wasted, an average increase of 7.4% for each order of inexpensive drugs.

To calculate the percentage of resulting dollar savings we compute the average savings per order of expensive medication and multiply that by the proportion of these orders. We subtract the increase in waste cost of an average inexpensive drug multiplied by the proportion of orders for the inexpensive drugs. The resulting difference is then divided by the cost of an average order,

$$\frac{\frac{1}{4}\cdot 22.2\%\cdot \$20 - \frac{3}{4}\cdot 7.4\%\cdot \$6.67}{\$10} \approx 7.4\%$$

For this example sequencing the more expensive medications later in the schedule results in a predicted savings of 7.4%.

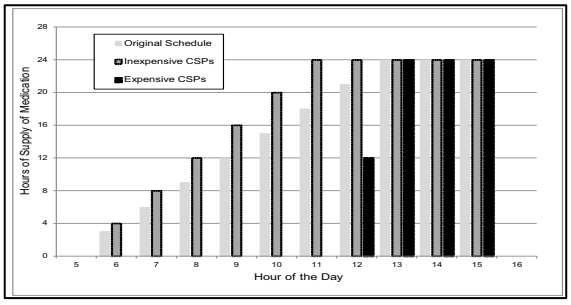

Figure 8. A Batch Preparation Inventory Diagram That Compares the Original and the New Schedule. Production of Expensive CSPs is Delayed; Production of Inexpensive CSPs is Completed Sooner

More generally, the cost reduction benefit from scheduling more expensive orders later is influenced by the proportion of expensive orders to inexpensive orders, and by the difference in the cost per dose. The larger the difference in costs, the larger the benefit from starting production of the more expensive doses later. Table 1 provides an example of expected reduction in waste for single batch production given the schedule assumptions in this section, and the discontinuation profile of our hospital.

Table 1. Waste Reduction Benefit from Delaying the Preparation of Expensive CSPs in a Batch

		Expensive CSP orders as percentage of all orders			
		12.5%	**25%**	**37.5%**	**50%**
Cost ratio expensive CSP dose to inexpensive CSP dose	**2**	3.0%	4.4%	4.7%	4.1%
	3	5.3%	7.4%	7.4%	6.1%
	4	7.3%	9.5%	9.1%	7.4%
	5	8.9%	11.1%	10.3%	8.2%
	6	10.3%	12.4%	11.2%	8.8%
	7	11.5%	13.3%	11.9%	9.2%
	8	12.5%	14.1%	12.5%	9.5%
	9	13.4%	14.8%	12.9%	9.8%
	10	14.2%	15.4%	13.3%	10.0%
	20	18.8%	18.4%	15.1%	11.1%

This example shows that adding data about the cost of CSP ingredients to the pharmacy data, and being able to generate work queues that can be ordered by the cost field could generate additional savings for the pharmacy. A more sophisticated information system could go further, generating the probability of an order being cancelled during the time of base preparation. This probability could be calculated based on parameters already available within the pharmacy database: such as the patient's ward, medication, the number of days the patient has been receiving the medication. The work can then be queued in order of increasing product of probability of order cancellation and the cost of the ingredients.

To further illustrate the principle we created a stylized Monte Carlo simulation. The simulation compares three modes of operation: preparing CSPs in a random order, preparing them in the order of increasing cost, and in the order of increasing cost multiplied by the probability of cancellation. Each trial simulates preparation of 500 doses. Each dose has the following attributes:

- unique index $j \in \{1,2,\dots,500\}$,
- random cost of ingredients k_j drawn from a uniform distribution on $[5,15]$,
- random probability of cancellation p_j drawn from a uniform distribution on $[0\%, 40\%]$,
- e_j, random error in the estimate of probability of cancellation p_j drawn from a uniform distribution on $[-40\%, 40\%]$,
- random variable $s_j \in \{0,1\}$ signifying whether the dose was cancelled, this variable is drawn

from a Bernoulli distribution with success probability p_j,

- random arrival of the cancellation order a_j drawn from a discrete uniform distribution on $[1,500]$,
- rank $r_j^1 \in \{1,2,\dots,500\}$, ranking the dose relative to the other doses in the order of increasing cost,
- rank $r_j^2 \in \{1,2,\dots,500\}$, ranking the dose relative to the other doses in the order of increasing index $p_j \cdot (100\% + e_j) \cdot k_j$
- rank $r_j^3 \in \{1,2,\dots,500\}$, ranking the dose relative to the other doses in the order of increasing index $p_j \cdot k_j$

A cancelled order is considered wasted in the random regime if the arrival time of the cancellation is after the dose preparation started, that is if $a_j \geq j$. When the preparation start time is based on ranking, a dose is considered wasted if $a_j \geq r_j$. So in each simulation trial, we calculate the number of doses wasted as $\sum_{j=1}^{500} If(a_j \geq r_j, 1,0)$, and the cost of waste as $\sum_{j=1}^{500} k_j \cdot If(a_j \geq r_j, 1,0)$.

Table 2. Results of Monte Carlo Simulation Experiments to Demonstrate Waste Reduction from Alternative Orders of CSP Preparation

Order of preparation	Waste	Mean	Stdev	MSE
Random, j	**Doses**	49.83	6.45	0.20
	$	498.52	67.98	2.15
Cost, r_j^1	**Doses**	49.90	6.56	0.21
	$	416.49	58.49	1.85
Index, r_j^2	**Doses**	35.96	5.63	0.18
	$	323.82	53.37	1.67
Index, r_j^3	**Doses**	34.95	5.89	0.19
	$	310.70	55.36	1.75
Num Cancelled Doses		99.78	8.90	0.28

We ran a simulation with 1000 trials. The statistics for the output waste variables are listed in Table 2. Ordering preparation using only the cost index does not reduce the number of doses wasted, but does reduce the cost of waste by 16.5%. With the numbers we used annual savings would amount to close to $30,000. Being able to estimate the probability of order cancellation and ordering dose preparation according to the cost and probability of a cancellation index would lead to further annual savings: an additional 21% in reducing waste associated with the cost of materials ($38,600 annually), and approximately 5400 fewer doses would be prepared annually, equivalent to approximately 180 employee hours. Even if the estimate of the probability of cancellation is within 40% of the actual value, the reduction in waste is still very close to the amount it would have been if the probabilities were known precisely.

6. Discussion and Conclusion

In introducing mathematical operations modeling to pharmacy managers Dean et al.[20] wrote, "Mathematical modeling offers pharmacists a low-risk, low-cost tool for aiding decisions about pharmacy systems by predicting alternative futures." One type of mathematical modeling, *computer simulation*, has been fairly widely used to guide operational decision-making in healthcare, including in pharmacies, as evidenced by several peer-reviewed publications [21-31]. Another type, *analytical modeling*, has not gained the same level of acceptance despite being easier to develop[20] than simulation models. Some well-known analytical models (e.g. the *economic order quantity* inventory management model) have long been used for the analysis and redesign of relatively simple processes in both manufacturing and service industries, including healthcare[32-34]**.** Working with an in-hospital pharmacy we demonstrated, the development and use of an analytical mathematical model to evaluate the performance of a variety of operational configurations for the preparation of compounded sterile products

We believe the insight and methodology used in our study could benefit many in-hospital pharmacies. For example, we calculated that shifting batch preparation to later on in the day, could save the hospital we worked with $71,900 annually. If the same savings were achievable in the 1100 other US teaching hospitals, nationwide annual savings could be close to $80 million. Interestingly, despite this potential benefit, we experienced challenges in attempting to disseminate this knowledge beyond our institution. On the one hand, the analytical model described here requires little mathematical sophistication (nothing beyond weighted averages and fairly straightforward data extraction), and is therefore too simple for the academic operations management journals. A realization of the model in a spreadsheet (e.g. in Microsoft® Excel) can be used by a manager to quickly test various implementation options and to discover the most promising ones. However, our attempts to publish it in journals aimed at pharmacy managers brought comments from the reviewers that the model would be too complicated for pharmacists. At the same time the reviewers expressed concerns about the validity of the model.

There are certainly some important limitations in our model. First, there is an assumption that use of the CSP inventory is constant over the 24-hour cycle. Because most institutions have standard drug administration times, the actual utilization will be more episodic with spikes of consumption throughout the day. With careful data collection, this variable can be incorporated in the model in a manner similar to the variable rate of order cancellations. However, we do not believe this assumption will have a large impact on prediction accuracy. Secondly, the model assumes that all discontinued orders lead to waste of the CSP. If the hospital is able to reuse some discontinued doses for other patients, the actual waste will be less than predicted. The model also assumes that every CSP order has an equal probability of being discontinued, and that the average cost is representative of those cancelled doses. Expensive CSPs (e.g., IV Immunoglobulin) prepared for a single dose order are unlikely to be prepared in advance and subsequently wasted. However, it is important to note that these doses are typically prepared outside of the routine batch in any case.

In our experience, despite the above limitations, this method proved accurate in predicting both the absolute number of wasted CSP doses and the reduction in waste from a new process implementation. Our mathematical model predicted that a 2-batch configuration considered in our institution with non-uniform size batches would reduce the number of discontinued wasted doses by 29.6%. Two 5-day physical waste audits were conducted pre- and post-implementation: these audits found that for the post two-batch implementation 33.3% fewer doses were wasted. We consider this a reasonable validation of the model. While recognizing some limitations of a model, it is important to keep in mind the words of the renowned statistician George E. P. Box, "essentially, all models are wrong, but some are useful"[35]. To slightly paraphrase Schlesinger and co-authors, who discussed validation of computer simulation models, model validation is a substantiation that a model possesses a *satisfactory* range of accuracy *consistent with its intended application*.[36] Further, as pointed out by Dean et al. [20] to determine the appropriate level of model validation, managers need to balance the cost of errors in the model's forecast against the cost of carrying out the validation.

The analysis of Big Data (i.e. petabytes of data) to gain new insights has garnered considerable attention recently. However, this case highlights that there are still opportunities for the application of insights from much smaller sets of operational data. Along with appropriate models these represent the 'low hanging fruit' of data analytics. The use of these sorts of techniques can also size the potential for savings or improvements. Thus, helping hospitals focus on the most promising areas and to set realistic objectives. However, it is also evident that the standardization of formats storing, sharing, and analyzing this sort of data is required if each hospital is not to be faced with reinventing the tools and approaches on their own.

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