MEASURING THE IMPACT OF DATA STANDARDS IN AN INTERNAL HOSPITAL SUPPLY SYSTEM

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ABSTRACT

Within a healthcare supply chain, the ability to trace and track patient care items through the use of unique identifiers has been shown to be a best practice. Data standardization through the use of Global Trade Item Numbers (GTIN) and Global Location Numbers (GLN) has helped hospitals improve patient safety and medical cost reimbursements. Despite these proven benefits the full adoption of data standards across all items throughout the industry has been slow to be achieved. This paper uses simulation to illustrate the potential benefits within a hospital supply system in terms of the improved management of items that can expire. By reducing the time and cost associated within expiration management, hospitals can show the benefits of data standards and justify the efforts to move towards a full adoption of data standards.

1 INTRODUCTION

Data standards, such as Global Trade Item Number (GTIN) and Global Location Number (GLN), have been proven effective in providing supply chain cost savings in industries such as retail and consumer goods. The Food and Drug Administration is establishing a national unique identification system based on a unique device identifier (UDI) to facilitate the identification and tracking of medical devices. According to the UDI Roadmap, the use of UDIs within the healthcare system can "lead to significant improvements in the ability to deliver high-quality, high-value care to patients". Significant efforts towards adoption of data standards in the healthcare industry started in 2006. Since then, various attempts to create adoption "deadlines" for healthcare providers have achieved mixed results. Currently, the strongest emphasis on adoption is focused around electronic data interchange (EDI) transactions and ordering processes.

This research has three main objectives: (1) identifying specific activities within the hospital supply chain impacted by global standards; (2) quantifying the benefits of adopting and utilizing global data standards within the healthcare supply chain; and (3) creating a representative analysis showing some of the operational benefits of exploiting data standards within a hospital supply chain. The goal is to show the potential benefits associated with standards adoption. The analysis enabled by this research assumes that the healthcare organization plans to implement data standards and would like to predict possible savings. Results are illustrated by documenting the benefits on specific activities within the hospital supply chain that are enabled by or influenced by global standards adoption, specifically within the area of expiration management. The primary focus is on the ordering, receiving, and inventory processes of a hospital inventory system, based on a simulation model of a partnering hospital provider.

This paper is structured as follows. First, we provide some background on the methods used to justify data standards within the literature. The focus of the review is to motivate the subsequent analysis. In

addition, we will overview some of the quantitative methods used in this area, with a particular emphasis on inventory modeling, perishable item management and simulation. Then, we will describe in detail the system to be modeled, our conceptual model, and the translated simulation model. This should provide a firm basis for interpreting the results. Then, we provide an overview of the experimental methods, the results, and their interpretation. Finally, we wrap up with some conclusions and ideas for future work.

2   BACKGROUND AND LITERATURE REVIEW

Healthcare supply chains have been slow in adopting data standards and technology when compared with supply chains in the retail sector. Jayaraman et al. (2015) state that current healthcare supply chain processes and practices are "often manual, ad-hoc, and outdated." They go on to state that the current state of the healthcare supply chain "offers abundant opportunities to provide tangible benefits such as cost savings, improve treatment outcomes, service quality, patient safety and satisfaction."

Data standards in the medical supply chain ensure interoperability of various systems across the supply chain, including external and internal processes, enabling effective exchange of information and increasing supply chain visibility. The utilization of data standards has impacts at the process level and affects the process related accuracy measures, exception rates and staff productivity among other performance metrics (Rossetti et al. 2012). The key components of the GS1 data standards are the Global Trade Identification Number (GTIN) and the Global Location Number (GLN). The GTIN is utilized for product identification, while the GLN is used to identify a products location. Together they increase visibility into the supply chain. The GTINS are a 14- digit code that provides a unique identifier for products across different units of measure. Secondary product information such as dimensions, pricing, expiration date, lot number and serial number can be incorporated into the code. The use of GTINs and the associated secondary information enables process automation, visibility and improved accuracy within the supply chain.

Franciscan Missionaries Health System implemented a fully automated GTIN order-to-cash process which resulted in reduced labor time and valuable space saving at the central distribution center (DC). The fully automated process directly benefited the inventory process and the labor value and indirectly benefited the recall product management and product tracking (GS1 AISBL (2016)). The health system experienced $52,000 in annual labor savings due to the fully automated process.

At the Florida Hospital Cardiovascular Institute, a Radio-Frequency Identification (RFID) inventory management system was implemented utilizing data standards (Tierney 2015) that resulted in the ability to better forecast demand of items, scan barcode items, better tracking and removal of recalled items, reduced overstock, and decreased overall spending. The RFID implementation directly benefited the ordering, receiving, and inventory process, and indirectly benefited the inventory forecasting, inventory spending, and outdated product management. The hospital experienced $1.7 million in annual savings from careful tracking and prediction of item demand, $5 million savings across the hospital's 13 labs, and an elimination of the expired medical devices within the inventory. The savings were determined through inventory control which led to the removal of thousands of dollars in expired devices from inventory.

Goyal and Griri (2001) provide a comprehensive look at modeling deteriorating inventory. Sharp and Pohl (2011) studied the effect of shelf-life on perishable goods supply chain costs. They developed a multi-period, three echelon supply chain with known demand. They utilized the model to examine tradeoffs between current production technology and more expensive production technology that resulted in extended shelf life. Perlman and Levner (2014) develop a multi-echelon, multi-supplier inventory model that integrates aspects of perishable and deteriorating products. They developed a network flow model that is used to analyze the trade-offs between the quantities of items to be ordered from regular and outsource suppliers. Their study confirmed that dedicated managerial effort is required to manage expiring products and ensure that they get to hospitals and do not expire in their distribution centers.

As the effects of data standards are analyzed, a key aspect that must be modeled is the inventory expiration process. There are many studies that utilize the deterioration of items such as food, electronics, and pharmaceuticals. For this study, the most common use of expiring product in a hospital environment is drugs. Wu et al. (2000) examined the deterioration of drugs being held in storage and found that a two-

parameter Weibull distribution is a reasonable model. Furthermore, Begum et al. (2009) utilized a three-parameter Weibull distribution to represent the life expectancy of items. This third parameter allowed for a shift in location as well as scale and shape and was determined by the authors to be the "most suitable for items that… start deteriorating only after a certain period of time". This representation is common when modeling the deterioration process of drugs. For the purposes of this paper, a three-parameter Weibull distribution $(1 - e^{-\alpha(t-\gamma)\beta})$ is used to model the expiration of inventory items in the hospital setting.

Several authors have used modeling and simulation as a tool to study healthcare supply chains. Rossetti and Liu (2009) simulated a multi-echelon multi-unit inventory system to study stock keeping proliferation in healthcare supply chains. Bonfanti (2016) used simulation models to analyze the effects of Unique Device Identification (UDI) on patient, doctor, and device manufacture related activities. Bedside patient care activities were shown to directly benefit and recall product management and patient safety were shown to indirectly benefited. The simulations showed the use of UDIs decrease patient deaths associated with recalled medical devices and improved device recall times.

3   MODELING THE HOSPITAL SUPPLY SYSTEM

In this section we provide an overview of the system to be simulated, the conceptual model, and the simulation model. The system being analyzed follows the ordering and processing of inventory within a hospital supply chain. In this system, a single hospital, consisting of many hospital units, is supported by an external distribution center (DC). The stock is stored at the external distribution center and will replenish the central storage unit (CSU) of the hospital after a delivery lead time. Inside the hospital, the CSU resupplies the hospital units. The inventory processes begin with incoming shipments from the DC to the CSU within the hospital. All packages received must be scanned and labeled for the invoice reconciliation to confirm package delivery. The items are stored in the CSU for later transport to individual hospital units. Once the unit level (UL) consumes all of an item, replenishment orders from the CSU inventory in the hospital are requested. Once the CSU runs low, a purchase order is made to restock the item from the DC.

The system has two main areas of interest- the central storage unit level (CSU) and the hospital unit level (UL). The CSU can be thought of as a large storage area within the hospital, while the UL can be conceptualized as smaller storage areas or closets inside of the hospital unit from which employees will retrieve what they need. Because the process for receiving, invoice reconciliation, CSU storage, reordering, UL storage, UL restocking, and UL reordering does not vary by product (item type), the focus of the modeling is a single item type. In addition, the processes do not substantially vary by the type of hospital unit being supplied by the CSU. Thus, a single UL location is incorporated into the model rather than many different hospital units. The extrapolation to many items can be readily achieved by varying the characteristics of the item (demand, inventory policies, lead time, etc.) and aggregating any cost analysis to the total number of items typically stored within a hospital. The processes modeled within the simulation are patterned on two hospitals within two healthcare supply chains. The main emphasis of the modeling is to investigate the effect of the use of data standards on the inventory processing, especially its potential benefits for impacting cost and performance within the area of expiration management.

3.1   Conceptual Modeling

Figure 1 provides an overview of the processes modeled within the simulation. Stock keeping units (SKU) at the CSU are modeled with a reorder point, reorder quantity (r, Q) inventory policy. When the reorder point for the SKU is reached, an order is placed to the DC. After a random lead time, the replenishment order is received at the CSU. In the figure, this is the first step of the process, where the items are unloaded, scanned into the inventory system, invoicing is checked, and any discrepancies between the receipts and invoices handled. Then, the items are placed within the CSU. After being placed in the CSU, any backorders from the units of the hospital are prepared for distribution to the units. At the unit level, inventory is managed using a periodic review period, order up to level inventory policy. Let T be the review period and let S be the order up to level. The (T, S) policy is extremely common within hospital inventory

management with the order up to level often referred to as the par level. The review period is almost always set to one day due to the convenience of managing such a policy. Thus, once a day, the inventory level for an item at the unit level is reviewed and if any usage occurs, a replenishment amount is placed to ensure that the par level is maintained. This review of the stocking position of the items at the unit level is typically performed by hospital supply chain personnel, often during the UL restocking processes. The UL restocking process involves the loading of inventory carts that carry material to the units. The items on the replenishment carts are restocked on the shelves during which time inventory cycle counting can occur as well as reviewing items for replenishment. Believe it or not this manual process is still prevalent within many hospital inventory management systems. In some more advanced systems, there is automation of the UL reordering and issuing via storage cabinets that keep track (through scanning systems) the usage and storage of items; however, the material still needs to be brought to the UL and the cabinets still need to be physically restocked.
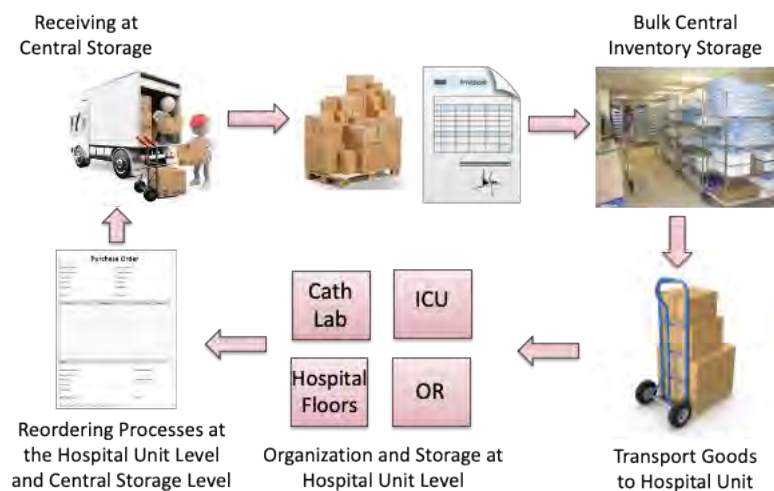

Figure 1: Conceptual overview of simulated processes

3.2 Simulation Modeling

The simulation model can be broken down into three aspects: UL operations, CSU operations, and expiration logic. Figure 2 presents the Arena model logic. In the figure, unit level inventory processing represents the arrival of demand to the UL. The unfilled demand is sent to the CSU for expedited processing. The unit level pick logic searches for unexpired inventory and picks the unexpired inventory. Items that are expired are recorded. In Figure 2, the unit level receiving logic processes the arrival of replenishment from the CSU. The items are dropped off for the put away process.

The replenishment also causes a check of the inventory level (due to the periodic review policy) and a sweep of expired items at the unit level. Activity within the model is triggered by processes that occur at the unit level. For this model, only one unit within the hospital was represented because all inventory operations are essentially the same for any hospital unit. The processes are triggered by an order arriving at the unit level. This represents a healthcare worker pulling an item off the shelf, or needing an item for a patient. This represents a demand for an item stored at the unit level. After the demand arrives, different variables and attributes are assigned to the order, and the model checks to see if there is enough of the item in the unit level inventory. If there is, the demand is filled and essentially leaves the model. If there is not enough inventory at the unit level, the model logic assigns whatever is available to the demand (partial fulfillment), and requests for the remaining amount of the order to be filled directly from the CSU level. The remaining quantity of the order is given an expedited value, so that once it reaches the central storage unit for the hospital it can be filled immediately to complete the order in a timely manner.
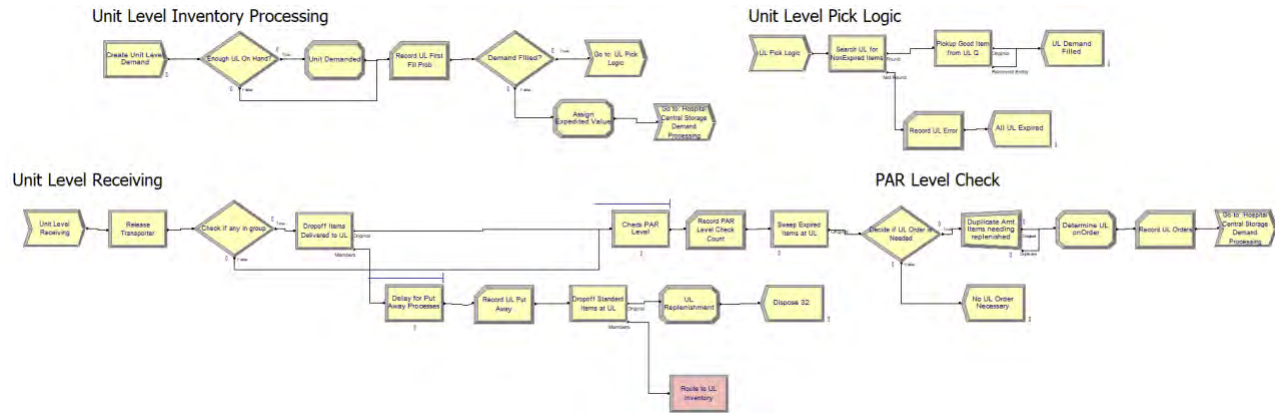
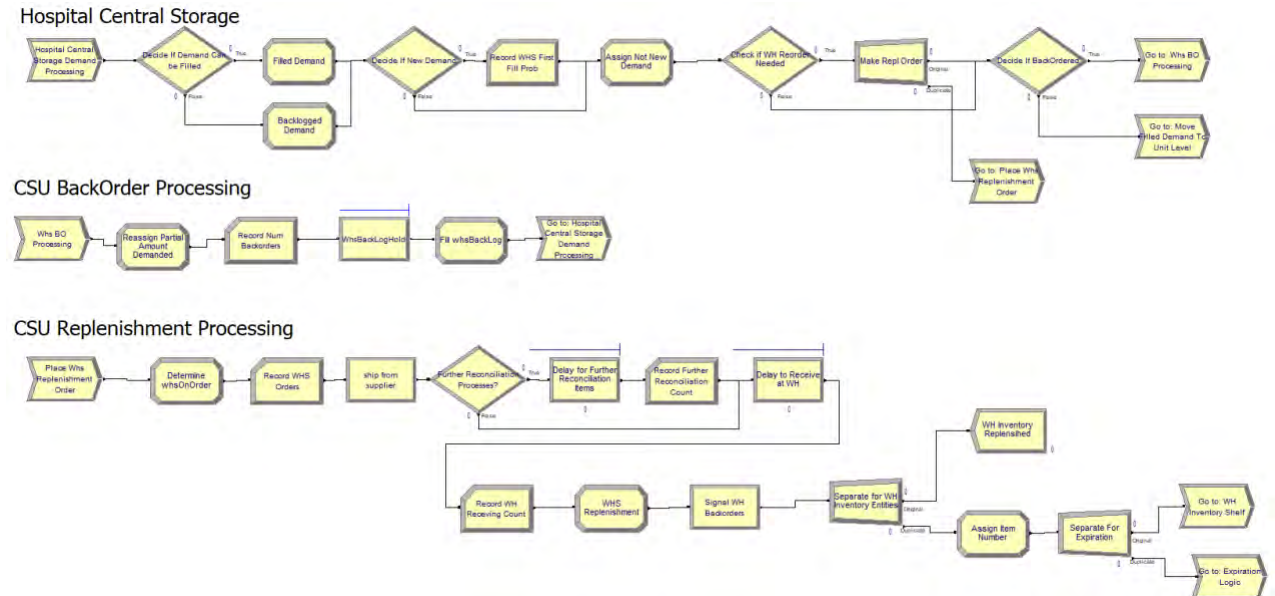Figure 2: Model logic for unit level processing

Figure 3: Central storage unit inventory processing

As previously noted, the timing of the UL replenishment process corresponds to the review period for the items stored at the unit. When the item is received at the UL, the worker will put the items away. These put away processes are implemented using a wait and signal construct within the model, with the signal scheduled to occur according to the periodic review period. Once the delivered items have been put away, the inventory levels will be updated. After the worker is finished putting away the items, they check the inventory level at the unit. This checking is based on a par level inventory system, where the worker is searching for products that have been used and need to be restocked. After completing this check, the order will be placed for products. For efficiency, the items that need restocking will arrive during the next UL replenishment (i.e. 24 hours later if the review period is 1 day).

Figure 3 presents the model logic associated with the CSU processing. The CSU operations begin when the order arrives from the unit level. The amount filled for the unit level replenishment order is the minimum between the CSU inventory level and the amount required so that the order can be partially filled. If the order is completely filled, the inventory levels are updated and the item is sent out to the unit level

replenishment processes. After the order is filled, it must be divided into either an expedited order or a regular order. If the order is expedited it is immediately transported to the unit level to satisfy the backorder at the unit level. If it is a regular order, it will enter a hold and wait for the once a day delivery by a central storage worker. Both expedited and regular orders must be packaged and transported by a central storage worker. If the order is not filled completely, the backordered amount is added to the backorder queue where it will wait until a delivery from the external distribution center signals that the backorder can be fulfilled. After an order is filled, it must be determined if the CSU needs to send a replenishment order for the product to the supplier. If a replenishment order is created, the arrival is delayed by the distribution center lead time and the inventory position state variables are updated accordingly.

In Figure 3 this logic is denoted by CSU Replenishment Processing. When a replenishment order arrives from the distribution center there are two routes for the receiving processes. Either the product can be received upon arrival, or further reconciliation processes are necessary. Some examples of further reconciliation include missing invoices or if a PO number is not seen on the package. The further reconciliation process takes longer than the typical receiving process; however, both are done by one of the receiving workers. Once the incoming material is received a signal is sent to the backorder processes, and the inventory state variables are updated.

The processing of demand that has been filled at the CSU level is indicated in Figure 4. This includes the searching and picking of good product and the disposal of expired product. If the picked items are for an expedited order from the UL, then the items are directly dropped off at the unit level. If the items are not expedited, they are held for the scheduled daily deliver to the UL. The daily check at the CSU level involves sweeping for expired product and picking, packing, and delivery of the items to the UL.
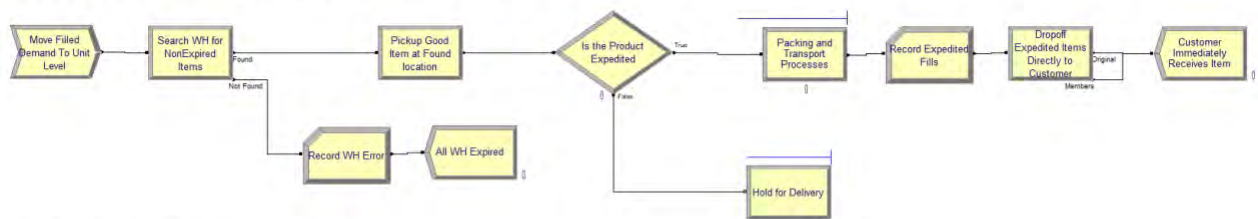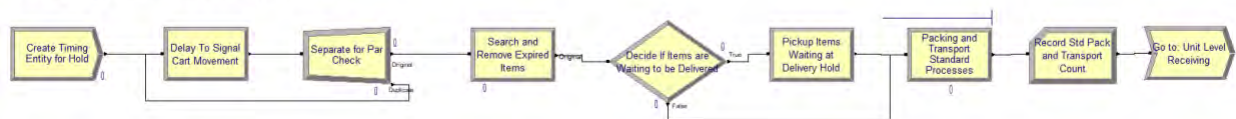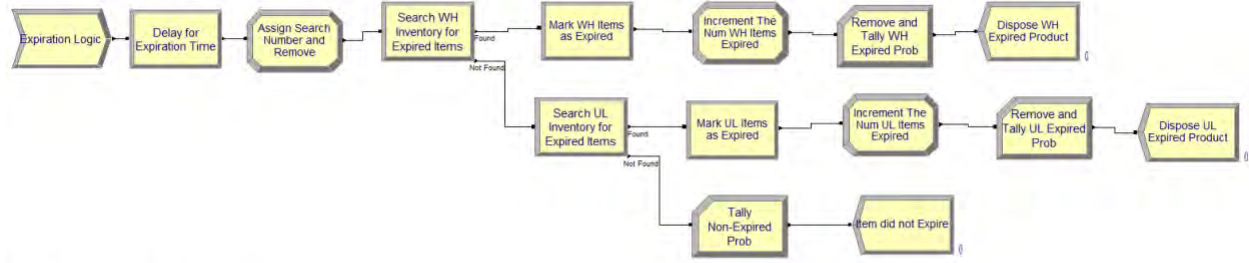

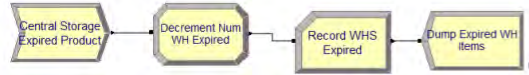Figure 4: Processing of filled orders at the CSU level

When the inventory is placed on the shelf, the expiration processes commence. As noted in Figure 5, when an item is placed in inventory, a duplicate of the item is created and scheduled to expire after a randomly determined expiration time. When the scheduled expiration event occurs, the inventory is checked to see if the item has already been used at the CSU level or at the unit level. If the corresponding item has not been used, the inventory has expired while being on the shelf and statistics collected on the amount of expiring items. At the CSU, there is a weekly sweep of the inventory to check for expired items.

If an item has expired while on the shelf, it will be removed. The removal of expiring items may cause the inventory position to go below the reorder point and if so a replenishment order is placed to the DC. When an item demand occurs at the UL, it is checked to see if it has expired, if it has expired, additional inventory is taken from the shelf. If insufficient inventory exists to fill the UL demand, an expedited order is placed at the CSU. Statistics are collected on the frequency of occurrence of expired product.
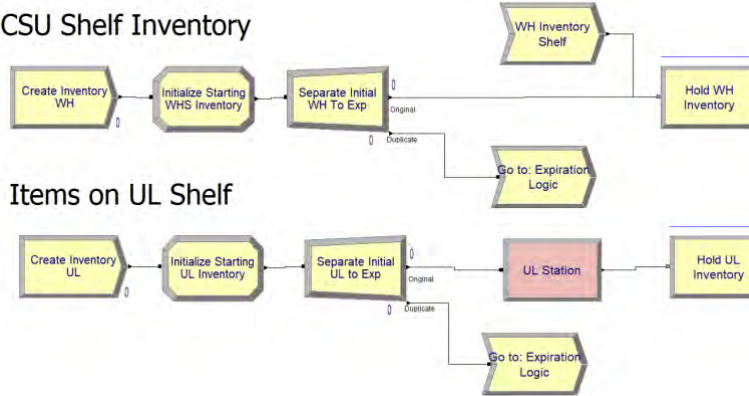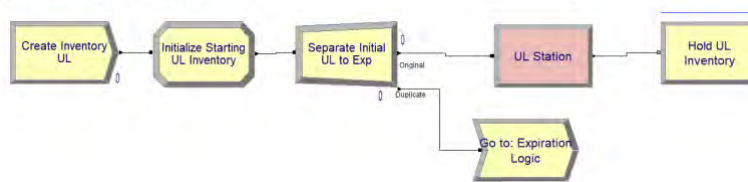
Figure 5: Product expiration logic

Figure 6: Loading the initial inventory on the shelves

The final modeling issue is the loading of initial inventory on the shelves. The model reads in the demand and lead time parameters from the experimental settings and using an approximation for the (r, Q) inventory policy and the (T, S) policy sets the policy parameters accordingly. Then the appropriate inventory is created to represent the required initial inventory levels. This creation process is illustrated in Figure 6. Entities representing inventory to be placed at the CSU level and the UL are created and the expiration logic initiated. Because we model perishable items, the inventory was modeled using Arena entities. Once the inventory is loaded into the system the demand processes commence.

3.3 Simulation Input and Output Parameters

This simulation model quantifies the differences in hospitals that utilize data standards and those that do not. Data standards (DS) are hypothesized to decrease the amount of inventory that expires, decrease the overall cost, as well as affect many other metrics. The key performance measures of interest can be seen in Table 1. Within Table 1, CSU refers to the central storage unit level and UL refers to the unit level.

The input parameters for the model consist of two major types: factors used to control the experimental investigation and environmental parameters. These experimental parameters can include factors such as unit cost, unit level demanded, and ordering costs. In order to compare the differences between data standards (DS) and non-data standards (NDS), a separate set of DS and NDS parameters were created. These factors seen in Table 2 are used to control the experimental conditions related to processes affected

by data standards. The base-line values of the parameters are based on observations from a local hospital system. The values for DS were set based on hypothesized changes due to implementation of data standards.

Table 1: Major performance measures of interest

Performance Measure	Description
CSU Expired Product	Number of expired products at the CSU level
UL Expired Product	Number of expired products at the unit level
Average CSU Inventory	Average amount of inventory that is being held at the CSU level
Average UL Inventory	Average amount of inventory that is held at the unit level
CSU First Fill Probability	Probability that the order is filled on the first try at the CSU level
UL First Fill Probability	Probability that the order is filled on the first try at the unit level
Avg CSU Expiration Period	Total time the product was expired in the CSU
Avg UL Expiration Period	Average total time the product was expired in the unit level
Num of Backorders	Number of times that orders were on back order
Num of Expedited Fills	Number of orders that had to be expedited
Further Reconciliation Count	Number of times reconciliation is required for orders to the CSU

Lastly, environmental parameters are provided in Table 3. These parameters vary based on environmental factors but would not change in relation to data standards. These factors were assigned a high and low value, and a full factorial experiment was created with these 5 factors (2^5) for both the DS and NDS models. For each experiment, 30 replications were completed, resulting 960 observations. The replication period of each experiment was two years (730 days), with a one-year warm up period (365 days).

Table 2: Input DS and NDS parameters

Factor	Value	Units	DS	NDS
Factor that alters the minimum value of the regular receiving lognormal distribution	120	Min	0.8	1.2
Factor that alters the standard deviation of the regular receiving lognormal distribution	16.499	Min	0.8	1.2
Factor that alters the probability of a receiving order at the CSU needing further reconciliation	8	%	0.5	1.0
Factor that alters the minimum value of the further reconciliation lognormal distribution	200	Min	0.8	1.2
Factor that alters the standard deviation of the further reconciliation lognormal distribution	20.548	Min	0.8	1.2
Inventory Queue Settings	-	-	FIFO	LIFO

Table 3: Input environmental parameters

Factor	Nominal Value	Units	Low	High
Distribution Center lead time	4.5	Days	4	16
Mean time between demand at the unit level	1.4	Days	1	6
Expiration delay location parameter	90	Days	30	150
Expiration delay shape	60	Days	30	90
Time between the review period for CSU inventory	0.8	Days	1	7

4   EXPERIMENTS AND RESULTS

As indicated in Table 1, there were eleven performance measures that were of particular interest in the experiments. These performance measures should display possible effects of the use of data standards within the modeled system. The first experiment that was completed was a simple comparison of these metrics and their basic statistical properties for the non-data standards (NDS) and data standards (DS) versions of the models. The mean, standard deviation, interquartile range, minimum, the first, second, and third quartile, and the maximum of every performance measure can be seen in Table 4. All experiments were run with common random numbers and based on 30 replications. From these results, we can note that there are clear differences between the model responses for the NDS case versus the DS case. For example, from the row labeled "CSU Expired Product", we can see that the amount of expired product when using data standards is lower than when not using data standards. Although the statistical significance of the statistical tests are a function of the number of samples (30 replications), it should be clear that the sample size was sufficient to discern the direction of the change, which is the important aspect of the analysis.

Table 4: Basic statistical properties of NDS and DS performance measures

Response		$\bar{x}$	s	IQR	$x_{(1)}$	$q_{0.25}$	$q_{0.50}$	$q_{0.75}$	$x_{(n)}$
CSU Expired Product	NDS	27.83	41.56	37.75	0	0	9.00	37.75	233.0
	DS	1.39	5.55	0	0	0	0	0	52.0
UL Expired Product	NDS	8.62	16.72	8.00	0	0	0	8.00	88.0
	DS	6.58	18.57	0	0	0	0	0	117.0
CSU Inventory Level	NDS	37.56	20.08	31.17	14.13	18.10	34.51	49.28	88.69
	DS	38.48	20.69	32.07	13.67	19.19	34.61	51.26	91.92
UL Inventory Level	NDS	13.60	3.77	6.24	0	9.68	14.71	15.92	22.69
	DS	13.28	4.56	6.85	0	8.99	14.72	15.83	23.22
CSU First Fill Prob	NDS	0.88	0.07	0.09	0.557	0.84	0.888	0.93	1.0
	DS	0.89	0.07	0.08	0.542	0.85	0.899	0.94	1.0
UL First Fill Prob	NDS	0.70	0.12	0.14	0	0.64	0.719	0.78	0.920
	DS	0.67	0.18	0.15	0	0.63	0.720	0.77	0.966
CSU Exp Period	NDS	20,323	54,127	19,418	0	0	5389	19,418	796,320
	DS	5,139	33,486	0	0	0	0	0	705,600
UL Expired Period	NDS	28,032	82,109	16,616	0	0	0	16,616	836,640
	DS	7,351	44,316	0	0	0	0	0	819,360
Num of Backorders	NDS	312.20	311.50	313.80	0	105.0	220.0	418.80	2,287
	DS	279.38	283.73	299.00	0	84.25	195.0	383.25	2,153
Num of Expedited Fills	NDS	450.20	367.90	625.80	17.0	114.30	388.5	740.00	1,463
	DS	468.00	366.10	630.50	10.0	119.30	431.5	749.80	1,340
Further Reconciliation	NDS	15.01	6.88	12.00	1.0	9.00	14.00	21.00	38.0
	DS	4.93	2.94	4.00	0.0	3.00	4.00	7.00	14.0

After viewing the basic statistical values of these performance measures, we desired to know if the differences between the mean of the two models (DS and NDS) were statistically significant. Paired equivalence tests were conducted, and the results can be seen in Table 5. The alternative hypothesis either stated that the difference between the DS and NDS mean was greater than or less than 0. If the test column states "> 0" then the case "DS mean greater than the NDS mean" ($\bar{x}_{ds} > \bar{x}_{nds}$) was evaluated, and if the column stated "< 0", then $\bar{x}_{ds} < \bar{x}_{nds}$ was tested. If the p-value of the test was less than 0.05, then it is determined that the null hypothesis of both means being equivalent can be rejected.

As seen in Table 5, the results indicate that all of the performance measures have statistically significant different means, whether the DS or NDS is greater. The amount of expired product at both the warehouse and unit level were found to be much less in the DS model than in the NDS model. The results indicate that the average amount of time that the product spent expired (CSU /UL Expired Period) was statistically less in the DS model. The total number of backorders and amount of reconciliation were also less for data standards scenario. We found that the average amount of inventory at the CSU level was greater in the DS model, but it was less in the DS model at the unit level. However, while both of these were found statistically significant, the actual values of these means are very similar, and have less than 1 unit difference (seen in column 6). This same relationship is seen with the first fill probability, where at the CSU level DS is greater and at the unit level DS is less. Again however, there is actually a very small difference between the sample means from the two models. The last performance measure in which DS was found to be statistically greater than NDS was the number of expedited fills. The results indicate that about 18 more orders occurred in DS than in NDS. While this was statistically significant, this is only about 4% more than the NDS model.

Table 5: Paired equivalence tests on performance measures between the NDS and DS models

Response	$\overline{x}_{ds}$	SE Mean	$\overline{x}_{nds}$	SE Mean	$\overline{x}_{ds} - \overline{x}_{nds}$	Test?	p-value
CSU Expired Product	1.387	0.179	27.826	1.341	-26.440	< 0	0.000
UL Expired Product	6.581	0.599	8.622	0.540	-2.041	< 0	0.000
CSU Inventory Level	38.484	0.668	37.563	0.648	0.921	> 0	0.000
UL Inventory Level	13.277	0.147	13.596	0.122	-0.319	< 0	0.000
CSU First Fill Prob	0.890	0.002	0.878	0.002	0.013	> 0	0.000
UL First Fill Prob	0.673	0.006	0.701	0.004	-0.028	< 0	0.000
CSU Exp Period	5,139.1	1,080.8	20,323	1,746.9	-15,184	< 0	0.000
UL Expired Period	7,351.5	1,430.3	28,032	2,650.1	-20,680	< 0	0.000
Num of Backorders	279.38	9.158	312.24	10.053	-32.862	< 0	0.004
Num of Expedited Fills	468.04	11.816	450.24	11.873	17.799	> 0	0.000
Further Reconciliation	4.927	0.095	15.01	0.222	-10.080	< 0	0.000

After evaluating the sample means of the two models, it became apparent that including data standards in the hospital storage system improved the overall averages of the performance measures. However, it was also important that data standards not only improve the sample mean, but also the level of variation that occurs within these measures as well. Therefore, tests of two variances were conducted on the performance measures between the two models. This test utilized a confidence level of 95% and was once again testing if the variance in the DS model was either greater than or less than the variance in the NDS model. This was done by taking a ratio of the two variances (s_{ds}/s_{nds}) and testing if this ratio was "> 1" or "< 1" which determined if the DS variance was greater than the NDS ($s_{ds} > s_{nds}$) or less than the NDS ($s_{ds} > s_{nds}$) respectively. If the p-value is less than 0.05, then the null hypothesis of equivalent standard deviations (s_{ds}/s_{nds} = 1) between the two models was rejected in favor of the alternative hypothesis. The results of these tests are provided in Table 6.

The results indicate that there is statistically significantly less variation in the DS model for CSU expired product, but no difference between standard deviations at the UL. There was also statistically significantly less variation at both the CSU and unit level for the average time of expired product in the DS model. There is also less variation for the amount of further reconciliations in the DS model. In addition, the results indicate that the standard deviation in the DS model is greater than the NDS for the average inventory at the unit level, but was not statistically significant at the CSU level, resulting in not rejecting the null hypothesis. This same pattern is seen with the first fill probability, as the UL has a higher DS standard deviation while the CSU level has statistically similar variations for both models. Lastly, the p-

value for both the number of backorders and the expedited fills are well above 0.05, so the null hypothesis once again was not rejected.

Table 6 Tests of two variances on performance measures between the NDS and DS models

Response	s_{ds}	$hw(ds)$	s_{nds}	$hw(nds)$	s_{ds}/s_{nds}	Test?	p-val
CSU Expired Product	5.547	0.985	41.557	2.906	0.133	< 1	0.000
UL Expired Product	18.568	1.758	16.723	1.185	1.110	> 1	0.091
Avg CSU Inventory	20.689	0.627	20.080	0.590	1.030	> 1	0.133
Avg UL Inventory	4.563	0.221	3.765	0.160	1.212	> 1	0.000
CSU First Fill Prob	0.068	0.003	0.072	0.003	0.948	< 1	0.103
UL First Fill Prob	0.183	0.014	0.120	0.012	1.520	> 1	0.000
Avg CSU Exp Period	33,486	16,913	54,127	15,467	0.619	< 1	0.032
Avg UL Expired Period	44,316	19,951	82,109	15,579	0.539	< 1	0.001
Num of Backorders	283.734	25.361	311.476	27.137	0.911	< 1	0.098
Num of Expedited Fills	366.103	10.076	367.859	10.554	0.995	< 1	0.418
Further Reconciliation	2.940	0.106	6.880	0.209	0.427	< 1	0.000

5   SUMMARY AND FUTURE RESEARCH

The simulation modeling presented in this paper is intended to provide quantitative results that illustrate the benefits of adopting data standards within healthcare organizations. From the results, we can conclude that the use of data standards can significantly reduce the amount of expired items both at the unit level and at the central storage level of a hospital supply system. This reduction is almost 95% for a single item within a single unit of a hospital. Since hospitals may carry thousands of items that can expire, the cost savings from the better expiration management opportunities could be substantial. In addition, we noted a significant reduction in reconciliation activities, which would also reduce cost. The performance differences (e.g. inventory levels, fill rate, etc.) were not negatively affected by the use of data standards. In fact, there was a reduction in the amount of backordering. However, there was an increase in the number of expedited fills required at the unit level, probably because the expiration sweep processes enabled by data standards caused inventory loss at the unit level that was not accounted for within the inventory policy setting methods used in the research. Future research should include a full experimental analysis of the impact of both the operating parameters and the environmental factors on the performance measures for both the data standards and non-data standards cases. Such a study could look at the sensitivity of the performance measures with respect to the factors and provide more insight into the robustness of the results under the two scenarios and varying environmental factors.

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