OPTIMIZING OUTPATIENT CANCER CENTER THROUGHPUT USING A SYSTEMS-BASED APPROACH

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On my honor as a University Student, I have neither given nor received unauthorized aid on this assignment as defined by the Honor Guidelines for Thesis-Related Assignments

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Optimizing Outpatient Cancer Infusion Center Throughput Using a Systems-Based Approach*

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Abstract—**Over the last 30 years, outpatient infusion centers have been constructed across the United States to meet rising demand for cancer care. While outpatient care is now commonplace, these clinics still struggle to achieve patient throughput levels that match demand for their services. Our study examined the infusion workflow at a central Virginia infusion center whose patient throughput rate in fiscal year 2022 fell in the second quartile of infusion centers nationwide. We collated qualitative stakeholder interviews and in-person observations with the center's quantitative patient appointment data, to conduct a holistic analysis. Next, we evaluated current throughput levels with process mapping and descriptive statistics. Finally, we used statistical analysis to propose a strategy for future throughput improvement that included a data-based pilot test. Our analysis confirmed a need for process improvement at the infusion center. We found that patient idle times, drug types, and staffing appeared to be the key factors impacting throughput. Additionally, our results showed that appointment buffer times and drug pre-mixing were the most leverageable factors on patient throughput. Next steps should focus on enhancing our predictive modeling and implementing our proposed throughput improvement solutions.**

Keywords - oncology, cancer care, throughput improvement, chair utilization, human factors, systems-based approach

I. Introduction

Cancer is a disease caused by uncontrolled growth of the body's cells. Roughly half of all cancer cases in the United States are treated with chemotherapies delivered via infusion therapy, the intravenous administration of liquid medication [1]. Although cancer survivorship has steadily risen since the 1990s, a recent study projected there will be a 50% increase in US cases between 2015 and 2050 [2,3]. In the coming years, infusion centers across the country will need to create additional treatment capacity to meet rising demand.

Increasing infusion center treatment capacity by improving workflow efficiency is a well-studied topic. The Infusion Efficiency Workgroup, led by the National Comprehensive Cancer Network, gathered data from over 30 US outpatient infusion centers to perform statistical analysis on current conditions and possible solutions to increase infusion efficiency [4]. Kim et al. identified long wait times as a key barrier to efficiency in a study at South Korea's largest medical institute, and found that a reservation system for appointment scheduling was able to decrease waiting times [5]. Rieb's study at the Massachusetts General Hospital found that, similar to Kim et al., the use of scheduling optimization software improved efficiency [6]. And, at the Taussig Cancer Center, Blackmer et al. tested additional technical solutions, including advanced preparation drug mixing methods, and were able to significantly reduce patient idle times [7].

While there are several strategies to increase efficiency, risks do exist. For example, overscheduling can hurt patients and staff by slowing operations down [8]. Software like iQueue exists to facilitate efficient appointment scheduling and mitigate risks. However, preparing infusion centers to meet future demand is not solely a technical problem; other factors must be examined when designing workflow improvement strategies.

Infusion centers must simultaneously optimize treatment efficiency and human factors like patient safety, patient satisfaction, and staff satisfaction. Kim et al. found that long wait times caused frustration for both patients and staff [5]. Aboumatar et al. also found that long wait times can be dangerous and stress-inducing for the immunocompromised cancer patient population [9]. Although patient satisfaction would likely improve with increased workflow efficiency, patients could still be negatively impacted if these improvements resulted in additional treatment errors. Future work must therefore balance the need to improve efficiency with the need to maintain patient safety standards.

From a staff perspective, registered nurses, patient care technicians, and licensed practical nurses are subjected to serious strain within infusion centers [10]. Compounding this issue, healthcare systems currently experience difficulty hiring nurses due to an aging nursing population, lagging nursing schools, and COVID-19 pandemic burnout [8,11]. It is imperative that future efforts to optimize infusion center workflows simultaneously prioritize reducing additional strain on staff. All stakeholders—staff, patients, and hospitals—stand to benefit, if efficiency can be increased while optimizing human factors.

Our research team studied current workflow conditions and used a systems-based throughput improvement approach at a central Virginia outpatient infusion center. The center operates for 11.5 hours on weekdays and 6.5 hours on Saturdays, with early and after-hours access for immunocompromised patients. The center has 45 infusion chairs and serves about 100 oncology and non-oncology patients per weekday [10]. Thus, the goal of our study was to define and model the current system state, identify key factors impacting efficiency, and propose a throughput improvement strategy that simultaneously accounted for other objectives and that could be pilot tested in the future.

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II. Methods

A. Overview

Based on dialogue with infusion center administrators and existing gaps in literature, our team identified the objectives of the study: to use a holistic, multidimensional, iterative approach to gain an understanding of the key levers affecting patient throughput across the center's infusion system, and to use this knowledge to propose a throughput improvement strategy that balances this improvement with staff and patient considerations. During the first stage of our research, we used observations, interviews, and exploratory data analysis to identify key variables impacting the center's workflow. The second stage was dedicated to analyzing the impact of variation in these levers. Overall, our project was iterative in nature, in response to constant dialogue with infusion center team members.

B. Direct Observations and Employee Interviews

The research team conducted direct observations on the various work roles in the central Virginia outpatient infusion center to understand the center's workflow. The first observation was conducted by all three team members in September 2022 for approximately 4-5 hours. We shadowed an infusion scheduler, nurse manager, and nurse, then received a full walkthrough of the pharmacy. Notes in bullet-point form were taken and team members discussed and compiled their findings.

The team then held five follow-up interviews with staff involved at every key level of the center's workflow, including: a front desk associate, an infusion nurse, an infusion nurse manager, a pharmacist, and an infusion scheduler. Each interview lasted 20-30 minutes and was held over the phone by two or more team members. One facilitated questions while the others took detailed bullet-point notes. These conversations served to clarify questions and allowed the employees to convey the perceived inefficiencies in each of their work roles. Themes were then extracted from the interviews by aggregating responses and examining patterns mentioned across the interviews. These themes were further developed in recurring conversations with infusion leadership. Observations and interviews were utilized in tandem to contextualize the infusion center data received for quantitative analyses.

The team conducted a final observation in November 2022 for about 3-4 hours. Our team shadowed three different infusion nurses and focused on monitoring identified inefficiencies and validating timestamp data received.

C. Process Mapping

The next step to understand the system holistically was to map the different workflows, process steps, and patient handoffs for a detailed representation of the infusion center. Using combined notes from the first observation, an initial process map was created to act as a simplified model of patient flow. Preliminary data analysis and interviews uncovered important model omissions like staff handoffs and data collection steps. In our final iteration, we combined additional observations and quantitative findings to create a multiple-lane process map model. This map included key workflows, expected durations for each step, idle times, and areas for improvement across all three lanes.

D. Electronic Health Record Data and Descriptive Statistics

Data for this study was exported from the center's electronic health record (EHR) and de-identified by health system employees. Several fiscal year 2022 datasets were made available for analysis: patient scheduling times, drug infusion times, and associated appointments. Data variety allowed for a multidimensional analysis and identification of improvement areas that aligned with the process map. Datasets ranged from 30,000-70,000 observations, with 15-30 variables linked by a unique identifier number. We used left joins to link the data together, using the most complete scheduling table as our primary dataset. Descriptive analysis was conducted to measure the current system state, including aggregating chair utilization hours to compare to national rates. We measured utilization as the mean daily proportion of the total chair hours used for infusions. For the sake of cleaner data and models, we removed weekends and only considered full 10-hour work days when calculating utilization rates. Each variable was explored in depth to observe trends, alignment with observations and interviews, and understand problem areas. Due to skewed distributions, the median was generally used and quartiles were used for variance calculations. The data also contained a large number of outliers. Communication with the health system staff confirmed the removal of extremely long observations, attributing them to input error. NA values throughout the datasets varied from 5%-30% for each timestamp value and this incompleteness was factored into the confidence of the analysis.

E. Statistical Modeling and Pilot Test Fit

Several levers for improvement were identified through statistical modeling in R and decision theory techniques. We used linear modeling, main effects, interaction, and tests of proportions to predict areas of interest across a range of continuous and categorical predictors. To identify predictor variables for our models, we used existing literature, correlation plots to prevent multicollinearity, and proportion tests to examine frequency. The categorical predictors were one-hot encoded for inclusion in our models. Diagnostic plots, including normality tests, Cook's distance, homoscedasticity, and linearity, were run on models and models were transformed accordingly if any were violated.

Criteria to compare models on predictive power included AIC, BIC, and R-squared values. The lower the AIC and BIC, the better fit the model was. Likewise, the higher the R-squared, the more variability was explained. P-values were used to measure significance for variables. We created a new dataset for our daily predictive model that calculated daily totals and medians for appointment duration, idle time, and chair time. We also removed NA values to run models, with the volume of NA values varying by model.

Tradeoff-based decision theory techniques in Microsoft Excel were used to determine drug pre-mixing candidates for a future pilot study. The list of over 70,000 drug infusions was simplified to 300 main drug names. Baseline statistics

measuring drug preparation and infusion time were calculated. Each variable was directionalized to determine best and worst values, normalized, and then weighted. We derived weights from staff input and sensitivity analysis. The score from each variable was totaled, and the drugs with the highest total score were listed as candidates for potential pilot tests.

Finally, our team held discussions with the infusion center leadership team to discuss future predictive modeling and pilot testing. These conversations revolved around logistics, human impacts of optimization strategies, discrepancies between our findings and clinician experiences, and other important considerations.

III. Results

A. Direct Observations and Interviews

Several recurring themes emerged across observations and staff interviews. These themes surfaced areas of inefficiency, methods for improvement, and several human factors.

Firstly, scheduling and appointment buffering operated under a simple standard. Schedulers stated that iQueue has successfully been used to significantly decrease wait times and increase throughput by 15% over the past 5 years. In iQueue, each appointment was categorized by its length (1 hour, 2 hours, 4 hours, etc.), but an extra 90 minutes was also added as a buffer for all pre-infusion steps. This standard buffer facilitated a simple scheduling workflow. It also acted as a potential barrier to increased throughput the buffer time was not being fully used. Staffers conveyed that the buffer duration was generalized and that some appointments did not in fact utilize the full 90-minute buffer.

The second major theme we observed was that lab and clinic appointments negatively affect patient experiences by increasing wait and idle times. Scheduling struggled to accommodate linked infusion appointments in an efficient manner, which caused patients to wait for prolonged periods due to each appointment's allocated buffer time. Additionally, primary care doctors sometimes caused additional slowdowns for the sake of safety, creating more idle time for patients. Observations showed that these extra steps were necessary to facilitate safety, but were also a barrier to efficiency and a quality patient experience in some instances.

Thirdly, the pharmacy operations appeared to operate as a black box and could account for a loss of efficiency. Non-pharmacy staff were frustrated that they lacked visibility delays caused by the drug preparation process. Nurses explained that drug preparation-related delays contributed to the strain they were experiencing. Ultimately, nurses expected drug preparation to take an hour, with patients sitting idly while waiting on medications. On the other hand, pharmacy workers were able to explain that delays can occur when several drug orders are placed simultaneously by pharmacists, creating a backlog within the pharmacy.

The last recurring theme discovered was that data quality suffered due to inaccuracy and incompleteness. We observed that data input methodologies varied by staff member. To that end, we observed that the collection of data was sometimes automated and sometimes not depending on nurse preferences and procedure type. Because operating procedures regarding data appeared not to be uniform, there were major disconnects within the datasets we received. We encountered these disconnects several times throughout our analysis of descriptive statistics and our statistical modeling.

B. Process Mapping

The process map detailed a workflow model from three essential perspectives: data collection, patient experience, and staff responsibilities. The patient and staff workflow proceeded together as follows: (1) patient appointment is scheduled by scheduler, (2) patient arrived and checked in with front desk staff, (3) patient waited in lobby, (4) patient had vital signs measured by patient care technician, (5) patient waited in lobby while triage nurse cleared patient, (6) patient was taken to chair by infusion nurse and patient was prepped, (7) patient had idle time in chair while drug was prepared, (8) patient received infusion from nurse, (9) patient sat idle for next infusion if needed, (10) patient reached end of the infusion and patient checked out with nurse. The workflow remained consistent across most patients, with the exception of an additional process step for patients who were required to meet laboratory parameters for treatment. These patients needed to conduct a pre-infusion lab test and wait for lab results after having their vitals measured (step 4), before proceeding through the rest of the infusion treatment steps.

C. Descriptive Statistics

Our analysis indicated that the infusion center had a relatively inefficient workflow, with its chair utilization rate falling in the second quartile of infusion centers nationwide [12]. In this case, the infusion center had 45 infusion chairs that were staffed by nurses for 10 hours a day, which resulted in a maximum theoretical daily capacity of 450 chair hours. The center scheduled an average of 290 hours of infusions per day, resulting in a scheduled utilization rate of 65%. The center had an actual utilization of 55%, or 245 chair hours, a 10% decrease from scheduled volume, mostly attributed to patients not meeting parameters for infusion treatment or "no-show" appointments.

We also explored system waiting times to examine avenues for process improvement. We calculated that the median waiting time between patient check-in and treatment start was 156 minutes. The median time patients spent in the waiting room was 12 minutes, but nearly a quarter of patients (24%) spent over 30 minutes in the waiting room. For 44% of patients who required pre-infusion laboratory tests, the median wait time for results was 61 minutes after accounting for outliers, demonstrating that lab testing presents a significant process bottleneck. On the pharmacy side, there was a median wait time before medications were ordered of 4 minutes, a median wait time between medication ordering and pharmacy verification of 4 minutes, and a median wait time between verification and the administration of medication of 41 minutes.

D. Statistical Modeling

Model I: Predicting Daily Chair Utilization

We performed a linear regression to model daily utilization hours with the predictor values found in Table I. The stepped-out interaction model outperformed all other created models with the lowest AIC and BIC statistics and an R-squared value of 0.63. These variables and their interactions explained over 60% of the variance in daily chair utilization. The overall regression of chair utilization hours was statistically significant ($p<2.2e-16$). There were several key takeaways based on coefficients in Table I. For every utilization hour increase per day, nurses had to work an hour and 11 minutes longer and non-nurse staff had to work 1 hour and 7 minutes more. For every hour of increased utilization, an average of 3.5 more associated pre-infusions existed per day, meaning that the count of pre-infusions per day contributed to chair utilization hours. For every utilization hour increase per day, the median check-in to med start time decreased by 30 seconds, indicating that reducing idle chair time increases chair utilization.

TABLE I. Model I Variable Breakdown

Predictor Variable Name	Coefficient	P-Value
Intercept	-43.836	0.322
NurseHours	1.183	<0.001
NonNurseHours	1.133	0.229
MedianCheckIntoMedStart	-0.517	0.532
AssociatedPreInfusions	3.461	<0.001
NurseHours:NonNurseHours	-0.008	0.120
NurseHours:AssociatedPre Infusions	-.010	0.029
NonNurseHours:MedianCheckIntoMedStart	0.019	0.110
NonNurseHours:AssociatedPreInfusions	-0.019	0.093

Model II: Predicting Chair Idle Time

Chair idle time was discovered as an area of potential improvement during process mapping, throughout exploratory analysis, and in Model I. "Idle chair time" was defined as the time between a patient being seated in an infusion chair and their medication start time. Various models were run, and the transformed stepped-out interaction model ended up having the both lowest AIC and BIC values and a R-squared of 0.201, which accounted for slightly more than 20% of the variance found. The model was also statistically significant ($p<2.2e-16$).

Model III: Predicting If Appointment Time Was Less Than Expected

A patient's appointment number showed the strongest relationship with appointments going significantly under their scheduled duration, through a variety of variables and interactions through tests of proportion, statistical models, and Chi-Squared tests. The "significantly going under" classification was derived from a complex model operating within the EHR, which set a bar for unacceptable differences between scheduled and actual appointment times. Of 3,683 first appointments, only 19.19% went significantly under the expected duration. Meanwhile, 30.5% of 23,523 follow-up appointments went under. We found that the percentage difference across a patient's appointment number was significant with a test of proportions ($p<0.00001$). There was an average of 82 follow-up appointments per day, and these appointments went under the scheduled duration by a median of 30 minutes. In a broader context, only 4.8% of the 23,523 total appointments went significantly over their scheduled duration. This indicates that the scheduled discrepancy was a one-sided issue from a percentage standpoint.

Model IV: Drug Pre-Preparation Decision Model

Lastly, we developed a drug pre-preparation pilot study to reduce idle chair time. We examined six main variables for each drug: number of administrations, median verification time, median prep time, standard deviation of prep time, median administration time, and standard deviation of administration time. Based on conversations with leadership staff and desired tradeoffs, the variables were assigned weights of: 0.12, 0.12, 0.28, 0.1, 0.28, and 0.1, respectively. Using these variables and weights, the drugs were ranked to identify which ones that were most fit for a pre-preparation pilot study. The top five candidates were ocrevus, istodax, arezerra, gazyva, and taxol.

IV. Discussion

A. Summary of Key Findings

Based on qualitative assessment of the center, four main themes emerged: buffer time scheduling, idle time issues, pharmacy efficiency, and data quality. Staff expressed a desire to improve utilization numbers by decreasing idle times. Using these themes and our observations, we categorized time negatively impacting overall efficiency as unscheduled time, waiting time, or idle time. Our process map also reflected similar findings. Statistical testing demonstrated that follow-up appointments go significantly under their expected duration 10% more frequently than first appointments. Model I found that 60% of variability in daily utilization could be explained by idle time, staffing hours, and pre-infusion volumes. Lastly, we found that ocrevus, istodax, arezerra, gazyva, and taxol were the five best candidates for a future drug pre-preparation pilot study. These several factors provided a holistic framework for understanding the center's patient throughput, and suggested several strategies for increased workflow efficiency moving forward.

B. Comparison to Previous Research

Similar to previous studies, our analysis demonstrated several potential avenues for improved efficiency within outpatient infusion centers. Like Kim et al., we found significant patient idle times at every stage of the infusion

process, including in the waiting room, during lab testing, and between check-in and medication start [5]. While we cannot directly compare our two studies' idle time metrics due to Kim et al.'s use of slightly different timestamps, our overall idle time results are consistent: patients spend lots of time waiting during the infusion process, and this waiting time is a significant problem for workflow efficiency. Moreover, the fact that our results are consistent despite our center treating less than half as many patients implies that idle times represent a significant bottleneck for workflow improvement across infusion centers of differing sizes.

Our center's prior success implementing iQueue mimicked successes seen in Kim et al. and Rieb's studies [5,6]. Our results confirmed that advanced scheduling techniques can improve throughput rates and decrease wait times. In particular, our Model III results suggest a modification to scheduling that goes beyond Kim et al. and Rieb and is, to our knowledge, novel: schedulers could improve efficiency by reducing scheduled buffer times, especially for follow-up appointments. More broadly, our study and Rieb's both approach throughput improvement by attempting to spread work more evenly across the workday. Our proposed drug preparation pilot test extends Rieb's approach beyond nurses to the pharmacy, where we observed that fluctuations in workload throughout the day can result in long drug preparation times.

To that end, our study's pharmacy observations were consistent with Blackman et al.'s findings because we also identified the pharmacy as a significant potential source for future efficiency gains [7]. Although the slate of drugs we proposed for a future pilot study differs from the drugs Blackman et al. tested, both of our studies prioritized including medications that were used with high frequency. We believe that the future drug pre-preparation pilot test will reduce drug preparation wait times while slightly increasing waste, consistent with Blackman et al.'s study.

On the human factors side, our observations of patient and staff preferences were also consistent with previous literature. Like Kim et al. and Aboumatar et al., we observed that lab and clinic wait times negatively affected patient satisfaction [5,9]. Similarly, consistent with prior work, we observed that nurses were under significant strain due to shortages at the center and in Virginia overall [11,13]. Overall, we feel that our study's systems-based approach to improved workflow efficiency produced a uniquely holistic consideration of quantitative and human factors in tandem.

C. Implications

While many inefficiencies exist within the infusion center's appointment workflow, utilization loss also occurs during the scheduling phase. Based on our analysis overall, there is significant potential for increased efficiency at the infusion center we studied. Additional work must be done if the center is meant to increase their treatment capacity to meet both current and future demand.

Our Model III results indicate that buffer time could be safely reduced by 10 minutes for all follow-up appointments. With this change, the overall distribution of follow-up appointments would still fall significantly under the scheduled time, with an average of 820 minutes of time savings per day. If schedulers filled this time with additional appointments, utilization would increase by 3%. This solution keeps patient safety constant because time savings are leveraged from unscheduled time rather than accelerations to existing nurse processes that might introduce human error. On a general note, our results indicate schedulers can save time by reducing follow-up appointment buffer times, but the ideal reduction will likely differ across infusion centers.

We also identified nurse hours as highly influencing chair utilization rates through both quantitative and qualitative analysis. Model I showed that increased nurse hours were correlated with increased utilization, likely because the center scheduled more appointments when more nurses were able to work. However, increasing nurse hours is not an easily implementable solution to improve utilization rates. Because of the COVID-19 pandemic, Virginia recently reported that 31% of its nursing facilities experienced one or more weekly staff shortages [13]. While exploring other avenues for throughput improvement, the reality of nursing shortages must be taken into account. Moreover, infusion centers must prioritize holding nurse satisfaction consistent or improving it while implementing throughput improvement strategies, to avoid further burnout problems.

Much of the other workflow inefficiencies we measured were a result of prolonged idle times. This dynamic was evidenced by Model I, which showed that median daily idle time decreased as daily utilization rose. However, as evidenced by our Model II results, idle time cannot directly explain more than 20% of the observed variance in utilization rates. Thus, the proposed pilot study will build off one of the observed themes and look to study whether drug pre-preparation towards the beginning of the workday is a feasible way to reduce idle time. Contextually, many of the pre-infusion drugs taken by patients require 30 minutes for administration before infusion treatment can begin. This means that if drug preparation times can be reduced from 60 to 30 minutes, patient idle time would drastically decrease, and patients with 30 minutes of pre-infusion treatment would experience virtually no idle time. Pre-preparing selected drugs for midday appointments during the early morning hours will likely increase drug preparation times for early appointments, while reducing drug preparation times for mid-day appointments. By spreading pharmacy work more evenly across the workday, we hope that overall idle times would significantly decrease and median drug preparation times would be much closer to 30 minutes. However, such a pilot also has some anticipated negative implications that would need to be monitored, including cost of waste and staff adoption of the methodology. The financial effect could be mitigated by financial returns from utilization increases, but the sustainability of the center would be negatively affected by such waste.

D. Limitations

Limitations in this research centered on project scope and data accuracy. As previously mentioned, some interviewees

conveyed inefficiencies created by primary doctor protocols and staffing shortages [10]. However, some instances are not as easily observable, as is the case for primary doctors. Likewise, some inefficiencies lack feasible solutions, as is evidenced by the ongoing nurse shortage. Solutions revolving around these areas were not investigated due to impracticality of suggesting meaningful change. Similarly, our work did not include weekends; we did not conduct observations on weekends and interviews communicated a slightly different workflow on weekends. Thus, outlined solutions should not automatically be extended to weekend workflow.

The largest limitation of our study was the lack of completeness and lack of reliable accuracy with data, as is explained by the fourth theme from observations and interviews. Many of the timestamp variables had missing data for at least 10% of observations. Some included missing values for up to 30% of observations or were redundant within the dataset. Additionally, certain observation identifiers were missing in certain datasets. Some datasets appeared to measure the same timestamps differently and with different values. Lastly, some data appeared invalid, which prompted conversations with leadership about data storage within the electronic health record and data collection within the center. Patient protection regulations limited the ability of our team to extract data and the bandwidth of health system staff was too thin to find or extract more accurate data within the timeframe of our project.

E. Future Research

Stemming from this study, future research can include the execution and evaluation of the proposed pilot study involving advanced drug preparation, especially regarding impacts of cost and potential waste. Future work could also examine buffer time modifications with more depth. Generally, future research should focus on how to improve data reliability and accuracy in order to make better utilization models with higher predictive power that incorporate more complex categorical variables. This could be completed by focusing on designing tools that can automate timestamp data collection within infusion workflows. Other factors that could be included and expanded upon are the inefficiencies in infusion centers that arise from laboratory and primary care relationships.

V. Conclusion

In order to understand how throughput can be improved in an outpatient infusion center, we utilized a systems-based approach to diagnose a central Virginia infusion center's workflow and target key areas of feasible improvement. We identified decreasing appointment buffer time and minimizing patient idle time as the main strategies for improving workflow efficiency. We also designed a pilot study to test drug pre-preparation as a method for reducing idle time. Future work should be completed in partnership with staff and patients to ensure improvements benefit every stakeholder and can be long-lasting.

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