Leveraging Health Informatics to Enhance Outpatient Chemotherapy Operations Management

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Abstract: The rise in demand for cancer care services, particularly outpatient chemotherapy, highlights the importance of improving the management of outpatient chemotherapy operations (OCOM). Despite the numerous studies addressing OCOM issues, the existing literature has mostly focused on problem-driven research. In this study, we aimed to utilize data-driven research to identify opportunities for improvement and address research challenges. To achieve this goal, we collected extensive operational data from a large chemotherapy center and performed a thorough analysis. Our findings revealed four key research challenges, including the prediction of length of stay, change in patient drug posting weight, delay in appointment admission, and stochasticity in drug administration duration. To address these challenges, we developed two machine learning models to predict these outcomes, utilizing 15 features and highlighting the most important features. Our results showed an efficient performance in predicting the outcomes using the XGBoost model, emphasizing the potential of data-driven research in improving OCOM.

1 INTRODUCTION

1.1 The Importance of Outpatient Chemotherapy Service (OCS)

Outpatient chemotherapy has been increasingly recognized as a cost-effective and convenient alternative to traditional inpatient chemotherapy. The significance of outpatient chemotherapy lies in its ability to provide patients with the same quality of care while reducing the burden of hospitalization. Outpatient chemotherapy was associated with lower costs, shorter hospital stays, and increased patient satisfaction compared to inpatient chemotherapy (Houts et al., 1984). This has important implications for health care systems as it can free up hospital beds, reduce wait times, and improve patient outcomes. Outpatient chemotherapy was not only associated with improved patient satisfaction, but also with improved clinical outcomes, as patients received their treatments in a timely manner without being admitted to the hospital (Waller et al., 2014). These findings highlight the importance of promoting and expanding the availability of outpatient chemotherapy services.

1.2 Operations Management (OM) Challenges in OCS

However, managing the operations of outpatient chemotherapy process presents several challenges. One major challenge is managing patient flow and ensuring that patients receive their treatment in a timely and efficient manner (Lamé et al., 2016). Additionally, managing inventory and ensuring that the right drugs are available at the right time is another significant challenge (Hadid et al., 2021). Moreover, managing the complex and dynamic nature of the outpatient setting, including unpredictable patient volume and the need for rapid adjustments to accommodate for changes in patient needs, can pose significant challenges for outpatient chemotherapy providers.

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1.3 Gaps in Outpatient Chemotherapy Operations Management (OCOM)

Despite the recognition of the importance of outpatient chemotherapy and the challenges associated with its operations management, there is still a gap in the literature related to effective strategies for managing the operations of outpatient chemotherapy facilities (Evans et al., 2016). The limited research has primarily focused on patient flow and wait times, rather than on the broader operations management issues associated with outpatient chemotherapy (Lamé et al., 2016).

There is also a lack of research on the impact of patient characteristics and behavior on the efficiency and effectiveness of outpatient chemotherapy operations (Ahmadi-Javid et al., 2017). Additionally, there is limited research on the use of advanced analytics and technology to improve the management of outpatient chemotherapy operations (Mandelbaum et al., 2019).

As technology continues to play a larger role in healthcare delivery, it is important to understand how it can be leveraged to improve the management of outpatient chemotherapy programs and support patients in their care. Although the use of data has the potential to greatly enhance decision-making in the operations management of outpatient chemotherapy, there has been limited research on the application of data analysis techniques in this field (Hadid et al., 2022).

1.4 Research Direction and Contribution

The key challenge lies in the effective utilization of the collected data to drive improvements in the operations management of outpatient chemotherapy, rather than just digitizing the process and analyzing the data. The ability to translate available data into concrete actions is what sets Data-Driven Operations Management Research (DDOMR) apart from other data-driven research, such as data-driven research of economists and statisticians or empirical Operations Management (OM) research (Simchi-Levi, 2013). Therefore, DDOMR has the potential to bridge the gap between prior studies and real-world operations by using data to identify areas for improvement and provide novel solutions (Gupta et al., 2021). This paper builds on this research direction and uses DDOMR to address gaps in the management of outpatient chemotherapy operations.

Through the collection and analysis of extensive data, this research identifies several avenues for further exploration, with a focus on using Machine Learning (ML) models to predict key outcomes and improve operations management. This study contributes to the development of new ML models that support decision-making and optimization in outpatient chemotherapy. The models developed and tested in this study show promising results in predicting length of stay, admission delay, changes in patient weight, and drug administration duration. Furthermore, the study highlights the importance of patient, drug, and process features in predicting these outcomes. This contribution provides a foundation for further research in this field and a roadmap for future improvements in the operations management of outpatient chemotherapy.

2 LITERATURE REVIEW

The literature on OCOM focuses on several key themes, primarily the optimization of patient flow through better appointment scheduling and planning, coordination between departments in outpatient chemotherapy centers, and resource allocation. Operations management scholars have approached these issues using various optimization and simulation models to improve a wide range of performance indicators (Lamé et al., 2016). The models used in the literature to optimize outpatient chemotherapy can be classified into deterministic, stochastic, and data-driven (Hadid et al., 2021).

The dearth of research in OCOM using cutting-edge data analytics such as ML models highlights a significant gap. Currently, no studies have combined ML models with decision support models in OCOM. Although, two studies (Mosa et al., 2021; Smith & Carlson, 2021) are relevant to the topic: the former predicts the risk of chemotherapy-induced nausea and vomiting using ML, while the latter suggests an ML-based approach to decrease emergency admissions due to chemotherapy side effects. This limited number of articles underscores the need for further data collection and utilization in OCOM research.

ML has been widely used in healthcare operations management, particularly in the field of cancer services. Numerous studies have shown its potential to improve the efficiency and quality of care provided to patients (Pianykh et al., 2020). For instance, ML algorithms have been used to predict the demand for certain cancer services, enabling healthcare organizations to manage their resources more effectively (Bastani et al., 2020) and providing more accurate and personalized care plans (Almeida & Tavares, 2020).

Nevertheless, despite its promising results, the integration of ML into healthcare operations management is still in its early stages and further research is needed to fully realize its potential. The search results from the Scopus database using the query in Table 1 indicate a gap in the use of ML models to improve the Outpatient Chemotherapy Process (OCP). Out of the 92 articles found, none used ML models to predict key factors affecting the OCP management. This further highlights the need for further research to utilize ML to improve the OCP (Hadid et al., 2021, 2022).

Table 1: The Search Query Used to Collect Articles from Scopus Database.

TITLE-ABS-KEY ("machine learn*" OR "artificial intelligence" OR "pattern* recognition*" OR "feature* selection*" OR "deep neural network" OR "deep learning" OR "convolutional neural network" OR "artificial neural network") AND TITLE (chemotherapy) AND TITLE-ABS-KEY (predict* OR forecast*) AND NOT TITLE-ABS-KEY (response)

This study aims to contribute to this research stream by developing new ML models that support decision-making and optimization in outpatient chemotherapy. The focus is on predicting patient behavior and key outcomes related to the administration of chemotherapy drugs, such as appointment delays, drug administration durations, and drug dose variation.

3 PROBLEM DESCRIPTION

We have conducted a time series analysis of operational data to uncover patterns and potential issues in daily activities. Figure 1 shows a significant difference between planned and actual patient admissions. The center allows early admissions to optimize bed utilization and hasten drug order activation and preparation processes. Patients are predominantly admitted at two time slots, 7 AM and 11 AM, with more patients arriving early for the 11 AM slot.

However, as depicted in Figure 2, the number of patients receiving the primary service of drug administration is significantly smaller compared to those waiting or receiving secondary services. During peak hours, the proportion of patients receiving drugs does not surpass 15% of the total number of patients in the center, which contradicts the expectations from allowing early admissions and punctual patient arrivals to reduce crowding and improve patient flow.

These factors make predicting the length of stay difficult, as shown in Figure 3. There are multiple medical and operational factors that contribute to the length of stay. The goal is not to study these factors, but to highlight the challenge in accurately predicting the length of stay, which is used as an input in appointment planning and scheduling. The drugs net infusion duration is not a representative of the length of stay, even if the expected time for a nurse to change the drug between drug infusions is added to it to calculate the total drug administration duration. Despite this, the total drug administration duration is still not a reliable predictor of the length of stay as shown in Figure 4.

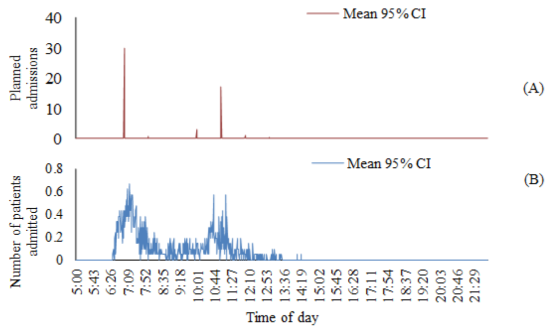

Figure 1: Average daily planned and actual admission patterns for one month.

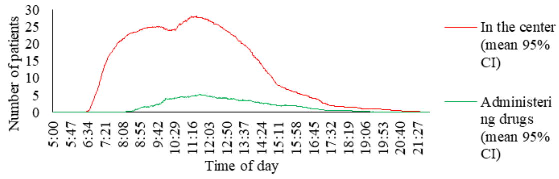

Figure 2: Average daily patterns of number of patients in the center and patients administering drugs for one month.

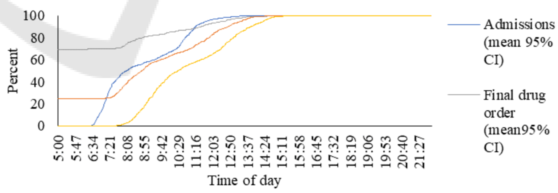

Figure 3: Average daily percentage of number of patients in main appointment stages over time for one month.

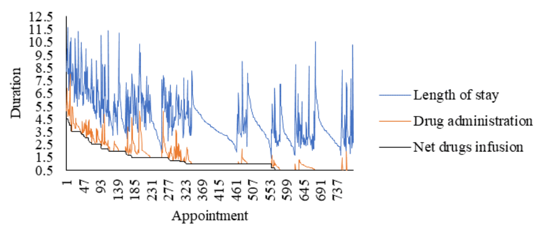

Figure 4: Comparison between length of stay, drug administration duration, and net drug infusion duration for 737 appointments.

Therefore, there is a need for predictive models to enhance decision support in outpatient chemotherapy. Our analysis highlights the importance of predicting four key factors: (1) change in patient body weight between dosing day and appointment day, (2) delay from the planned admission time, (3) drug administration duration, and (4) length of stay. These predictions are crucial for all departments involved, particularly pharmacy and day care, as they can assist in improving the accuracy of drug preparation and scheduling. The prediction of changes in weight and expected admission delays can help the pharmacy increase the number of drugs prepared in advance. Predictive models for drug administration duration and length of stay can improve scheduling efficiency and increase capacity utilization. Consequently, this will reduce the gap between the percentage of drug orders dispensed and the percentage of drug orders initiated for administration, ultimately reducing the number of patients present in the clinic during the day.

4 METHODOLOGY

As discussed in the previous section, we aim to demonstrate the potential of using ML models to support decision making in outpatient chemotherapy centers by predicting four important outcomes: (1) change in patient body weight, (2) length of stay, (3) admission delay, and (4) total drug administration duration. The following subsections presents the data preparation and model development steps.

4.1 Feature Selection

We identified the following features for our ML models: age, gender, body weight, oral body temperature, height, respiratory rate, blood pressure, type of drugs used (9 categories), drug administration duration for all cycles (1 to n-1), cancer type (oncology or hematology), number of drugs used, appointment slot (morning or afternoon), prior notice for appointment in days, and day of appointment (Sunday to Thursday). The type of drugs was encoded into 9 categories, and days of appointment were encoded into 5 categories, resulting in a total of 26 distinct features for predicting the desired outcomes.

4.2 Dataset

The dataset used for each of the four outcomes consisted of 1121 rows of encounter details, 26 features, and the target outcome. However, due to the presence of 817 missing values in the body weight feature, only 304 encounter details were used to build the predictive model for body weight variation. For the other three outcomes, all 1121 data points were utilized.

4.3 Data Preprocessing and Model Building

For features with less than 20% missing values, KNN imputation was used to estimate the missing values. To predict all four outcomes, we developed linear regression and Xgboost regression models by splitting the available data into 80-20 train-test splits. The predictive models were developed using the scikit-learn library in Python, and the mean absolute error metric was used to evaluate their performance on the 20% test data set.

5 RESULTS AND DISCUSSION

5.1 Predication of the Length of Stay

The length of stay of a patient is a crucial factor in the management of hospital resources and bed capacity. The traditional approach of estimating length of stay by adding a fixed time to the drug infusion duration is often insufficient in accurately predicting the actual length of stay. This can lead to inefficiencies in bed management and potentially result in overbooking or underutilization of resources.

To address this issue, a ML model was developed in this study to predict length of stay more accurately. The model was trained on patient and process data, including features such as age, height, blood pressure, days to the appointment, number of drugs, temperature, respiratory rate, cancer type (tumor or blood cancer), drug infusion durations, day of appointment, and type of drug. Results from the study showed that these features are relevant for predicting length of stay (Figure 5).

The utilization of this ML model will allow schedulers to make more informed decisions and accurately estimate length of stay, leading to a more efficient management of bed capacityPredication of the body weight variation

The process of determining the appropriate dosage of drugs for patients is a critical aspect in oncology treatment. One of the factors that affects the dose is the change in the patient's body weight. In order to calculate the percentage change in body weight, the difference between the dosing weight and the measured weight on the appointment day is divided by the dosing weight and multiplied by 100.

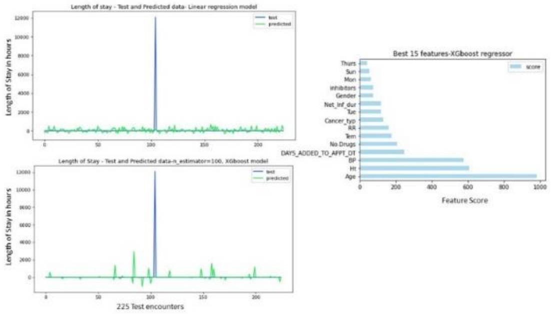

Figure 5: Actual and predicted values of length of stay using the two models as well as the top 15 relevant features to predict the outcome.

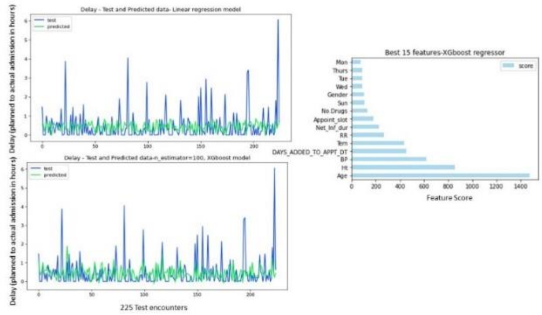

Figure 7: Actual and predicted values of delay between planned and actual admission using the two models as well as the top 15 relevant features to predict the outcome.

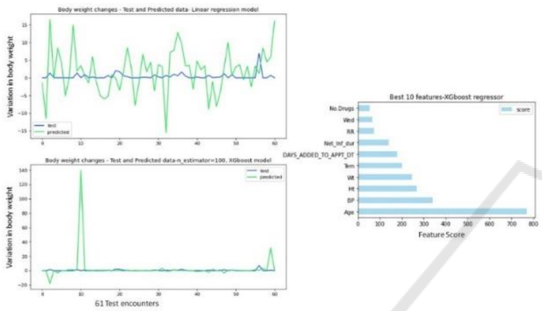

Figure 6: Actual and predicted values of body weight variation using the two models as well as the 10 most relevant features with respect to the outcome.

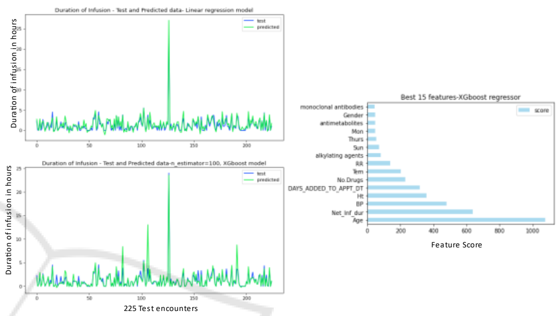

Figure 8: Actual and predicted values of drug administration duration using the two models as well as the top 15 relevant features to predict the outcome.

The dosing day, which is usually before the appointment day, is when the patient comes to the center to be seen by the oncologist and have his weight measured and drug order placed. However, the patient's weight may change before the appointment day due to various reasons. As a result, the nurse checks the weight on the appointment day to confirm that it is still within 5% error and the same drug order is still valid.

The pharmacy does not prepare the drugs before the weight is measured due to the possibility of a weight change greater than 5% and the subsequent waste of the prepared drug. Therefore, to predict the change in body weight more accurately, the XGboost model was used, which showed better and more accurate predictions compared to the linear regression model (Figure 6). The most important features for prediction were found to be age, vital signs, and the number of days between the dosing and appointment days.

5.2 Predication of Admission Delay

The results of predicting admission delay are presented in Figure 7. The performance of two models, linear regression and XGboost, is evaluated on a test dataset. The results highlight the importance of considering different factors that may influence admission delay. One of these factors is the appointment slot, which can either be 7 am or 11 am. This factor is found to be relevant to admission delay and can be used to enhance the overall patient experience by improving the scheduling system.

Another important factor is the number of days between the date when the patient was notified about the appointment and the actual appointment date. This factor can provide insights into the patient's behavior and how early or late they are notified about the appointment. These results highlight the significance of studying patient behavior based on the appointment time and notification date, which can provide valuable information for optimizing the scheduling system.

5.3 Predication of Drug Administration Duration

In an outpatient chemotherapy center, beds and infusion chairs are critical resources. Predicting the length of stay of patients in these resources is crucial for efficient resource management. Although the net duration of drug infusion is known and fixed, patients may require additional time during administration due to the preparation and removal of the drip, monitoring of their health status, and post-infusion observation.

Figure 8 highlights that the type of drugs being administered, such as monoclonal antibodies, antimetabolites, and alkylating agents, are among the top 15 relevant features that impact the drug administration duration. This highlights the importance of considering these factors when predicting the drug administration duration in the beds and infusion chairs.

5.4 Comparison of Models

In this study, the results demonstrate the potential of using ML models for improved decision-making in outpatient chemotherapy centers. As shown in Table 2, the Xgboost model performed better than linear regression in terms of mean absolute error (MAE), suggesting its effectiveness in predicting outcomes. However, it is worth noting that a simple linear regression model was also able to provide meaningful predictions, indicating that the suggested operational characteristics (OC) features and ML models can provide valuable insights.

Table 2: Performance of the ML models for four outcomes for outpatient chemotherapy operations management.

	Mean Absolute error			
	Length of stay	Body weight variation	Delay	Infusion duration
Linear regression	205.17	4.99	0.46	0.48
Xgboost	134.23	3.95	0.43	0.32

Despite the positive results, it is important to acknowledge the limitations of this study. One such limitation is the classification of drugs into 9 categories, which was based on mechanism of action and compound type. However, many drugs have overlapping features and were not accounted for in the classification process. For example, drugs like ado-trastuzumab emtansine and brentuximab vedotin have properties of both monoclonal antibodies and cytotoxic drugs, but were classified under monoclonal antibodies for simplicity. Additionally, the number of drugs used was accounted for in the feature "number of drugs", but the frequency of use of each type of drug was not considered. Furthermore, the ML models used in this study may benefit from further fine-tuning of hyperparameters. Addressing these limitations has the potential to further enhance the overall performance of the models.

6 CONCLUSION

In conclusion, the present study aims to address the gap in data-driven research in outpatient chemotherapy (OCOM) operations management. Extensive data was collected, and research opportunities were identified. In particular, the use of ML models, was thoroughly explored and tested. The results show that XGboost model outperformed linear regression in terms of mean absolute error in predicting admission delay and drug administration duration. These findings demonstrate the potential of using ML models in OCOM to improve decision-making, resource allocation, and patient satisfaction. However, the study also highlights some limitations and avenues for future improvement. Further research is needed to address these limitations and fully harness the potential of data analytics and ML in OCOM field.

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