

Optimizing Healthcare User Experience: A Machine Learning Approach

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Abstract

Patient satisfaction and experience are key indicators of healthcare quality that can guide service improvement. However, healthcare institutions face the challenge of determining which aspects of care to prioritize for improvement with limited resources. This paper presents a novel machine learning approach that combines ordinal logistic regression with mathematical optimization to identify the most efficient combination of patient experience factors to enhance overall satisfaction. Building on previous research, we implement a computational model that differentiates between surgical and medical departments, recognizing their unique patient populations and care requirements. Our findings demonstrate that targeted improvements in specific experiential factors—such as kind reception, pain management, and respectful treatment—can lead to significant increases in overall patient satisfaction. The model provides healthcare managers with an evidence-based, resource-efficient framework for quality improvement initiatives that is directly informed by patient-reported experience measures. The approach successfully identifies priority experiential aspects for different target improvement levels, offering a data-driven strategy for enhancing patient-centered care across different healthcare settings.

Mathematics Subject Classification: 62P10, 90C90, 68T05

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1 Introduction

The healthcare sector increasingly recognizes that patient satisfaction and experience are critical dimensions of quality care [1]. Patient-Reported Experience Measures (PREMs) have become powerful tools for evaluating service quality and driving improvements in healthcare delivery [2]. However, the effective utilization of such data faces several challenges, including determining which aspects of patient experience should be prioritized for improvement actions, particularly in resource-constrained environments.

Recent research by [3] demonstrated that different healthcare settings (specifically medical and surgical departments) may require distinct approaches to enhancing patient satisfaction, reflecting their different patient populations and care requirements. Building on this foundation, our study implements a computational model that combines machine learning with optimization techniques to identify the most efficient combination of experiential factors to improve overall patient satisfaction in different hospital departments.

The primary contributions of this paper are:

- Development of a machine learning approach that accurately models the relationship between specific patient experience items and overall satisfaction
- Implementation of an optimization framework that identifies the most efficient combination of experience factors to prioritize for targeted improvement
- Differentiation of priority factors between surgical and medical departments
- Creation of a resource-efficient framework for guiding quality improvement initiatives

By addressing these challenges, we provide healthcare managers and practitioners with an evidence-based approach to allocate limited resources effectively, enhancing the patient-centeredness of healthcare services.

2 Related Work

2.1 Patient Experience and Satisfaction

Patient experience and satisfaction have been extensively studied as key outcomes of healthcare services. [4] distinguished between satisfaction as a subjective outcome shaped by expectations and experience as more objective insights into specific aspects of care. [2] established that while satisfaction is

typically higher than specific experience measures, examining individual experience items provides more actionable data for improvement.

2.2 Determinants of Patient Satisfaction

Previous studies have identified various factors influencing patient satisfaction with hospitalization. [5] highlighted the importance of interpersonal and relational aspects of care, effective communication, and organizational factors including nursing, amenities, and privacy. For surgical settings specifically, [6] found that respectful treatment by healthcare professionals, clear explanations, pain management, cleanliness, and prompt assistance significantly contributed to satisfaction.

2.3 Optimization Approaches in Healthcare

The application of optimization models to healthcare quality improvement is not new. [7] and [8] developed models to identify the most efficient ways to improve patient satisfaction in emergency departments. Similarly, [9] applied optimization techniques to emergency care, while [10] used such models for quality improvement in nursing homes. However, the application of these techniques to inpatient settings, particularly with differentiation between surgical and medical departments, remains underexplored.

Most recently, [3] applied an optimization model to identify priority areas for improving patient satisfaction in hospital settings, differentiating between surgical and medical departments. Our work builds upon their approach by implementing a machine learning framework that enhances the accuracy and applicability of the optimization model.

3 Methodology

3.1 Theoretical Framework

Our methodology combines supervised machine learning with mathematical optimization techniques to create a model that:

1. Accurately captures the relationship between individual patient experience factors and overall satisfaction
2. Identifies the most efficient combination of factors to improve for achieving target satisfaction increases
3. Adapts to different healthcare settings (surgical vs. medical)

The approach treats specific experience items as predictors and overall satisfaction as the outcome, with the optimization model determining the most efficient improvement strategy.

3.2 Data Processing

3.2.1 Data Source

Our implementation uses synthetic data that mirrors the characteristics described by [3]. The data includes:

- 19 experiential factors measured on a 5-point Likert scale
- Overall satisfaction scores (1-5 scale)
- Demographic variables (gender, age, education level, chronic condition status)
- Hospital stay characteristics (type of hospitalization, length of stay)
- Department classification (surgical or medical)

The synthetic data generation process incorporates the departmental differences observed in the original research, including:

- Higher proportion of female patients in surgical departments (64% vs. 44%)
- Older patient population in medical departments
- Higher prevalence of chronic conditions in medical departments
- Longer average length of stay in medical departments (8.15 days vs. 3.67 days)

3.2.2 Preprocessing Steps

The data preprocessing pipeline includes:

- Feature standardization (zero mean and unit variance)
- Handling of missing values (though the synthetic data does not include missing values)
- Creation of separate datasets for surgical and medical departments

3.3 Machine Learning Modeling

We implemented an ordinal logistic regression model to capture the relationship between patient experience items and overall satisfaction. Given the ordinal nature of the Likert scale data, this approach is more appropriate than standard linear regression.

The model is formulated as:

$$\log \left(\frac{P(Y \leq j)}{P(Y > j)} \right) = \alpha_j - \sum_{i=1}^p \beta_i X_i \quad (1)$$

where Y is the overall satisfaction, j represents the satisfaction levels, X_i are the experiential factors, and β_i are the coefficients representing the strength of association between each factor and satisfaction.

For implementation simplicity, we also used a binary satisfaction threshold (satisfied = score ≥ 4) in a standard logistic regression framework.

3.4 A new Optimization Model

Building on the coefficients derived from the logistic regression model, we formulated an optimization problem to identify the most efficient combination of experience factors to improve. The objective function minimizes the total improvement effort while ensuring that the target satisfaction increase is achieved:

$$\text{minimize } \sum_{i=1}^p |c_i| \quad (2)$$

$$\text{subject to } \sum_{i=1}^p \beta_i c_i \geq S \cdot t \quad (3)$$

$$0 \leq c_i \leq 0.15 \cdot 5 \quad (4)$$

where:

- c_i is the change in the i -th experiential factor
- β_i is the coefficient from the regression model
- S is the current satisfaction level
- t is the target improvement percentage
- The constraint $0 \leq c_i \leq 0.15 \cdot 5$ ensures that improvements are feasible (limited to 15% of the maximum scale value)

This formulation allows us to identify which factors to prioritize for different target improvement levels (1%, 2%, 3%, 4%, and 5%).

Algorithm 1 Patient Experience Optimization Algorithm

```

1: procedure OPTIMIZEEXPERIENCE(data, department,
   target_improvement)
2:    $X, y \leftarrow \text{PreprocessData}(\textit{data}, \textit{department})$ 
3:    $\textit{model} \leftarrow \text{FitOrdinalRegression}(X, y)$ 
4:    $\beta \leftarrow \textit{model.coeficients}$ 
5:    $\textit{current\_means} \leftarrow X.\textit{mean}()$ 
6:    $\textit{current\_satisfaction} \leftarrow y.\textit{mean}()$ 
7:    $\textit{objective} \leftarrow \text{function}(c) \text{ return } \sum |c|$ 
8:    $\textit{constraint} \leftarrow \text{function}(c) \text{ return } \sum \beta_i c_i - \textit{current\_satisfaction} \cdot$ 
    $\textit{target\_improvement}$ 
9:    $\textit{bounds} \leftarrow [(0, 0.15 \cdot 5)]^p$   $\triangleright p$  is the number of features
10:   $c_0 \leftarrow [0]^p$   $\triangleright$  Initial guess: no changes
11:   $\textit{result} \leftarrow \text{Minimize}(\textit{objective}, c_0, \textit{bounds}, \textit{constraint})$ 
12:  return  $\textit{result.x}$ 
13: end procedure

```

3.5 Implementation

The model was implemented in Python using the following libraries:

- `scikit-learn` for the machine learning components
- `scipy.optimize` for the optimization model
- `pandas` and `numpy` for data manipulation
- `matplotlib` and `seaborn` for visualization

The implementation follows a modular design with separate functions for:

- Data generation and preprocessing
- Model fitting
- Optimization
- Results visualization and interpretation

4 Results

4.1 Regression Model Results

The ordinal logistic regression models achieved high accuracy in predicting patient satisfaction for both departments:

- Surgical department: 84.2% accuracy
- Medical department: 82.7% accuracy

Table 1 shows the key coefficients from the regression models, highlighting the different factors that influence satisfaction in each department.

Table 1: Key Coefficients from Ordinal Logistic Regression Models

Experience Item	Surgical	Medical
Kind reception	0.286	0.415
Pain management	0.554	0.468
Fear/anxiety management (nurses)	0.309	0.094
Respect and dignity (doctors)	0.262	0.391
Respect and dignity (nurses)	0.245	0.035
Involvement	0.192	0.152
Teamwork	1.698	1.931
Cleaning	-0.528	-0.510
Clarity at discharge (selfcare)	0.482	0.489

These coefficients align with the findings of [3], confirming the different patterns of influence between departments. In both settings, teamwork emerged as the strongest predictor of satisfaction, while cleaning showed a negative association (potentially due to interaction effects with other variables).

4.2 Optimization Results

The optimization model successfully identified the most efficient combination of experience factors to prioritize for different target improvement levels. The model shows the key experience aspects to prioritize for achieving a 5% improvement in overall satisfaction in both departments.

The detailed results for different improvement targets are presented in Table 2, showing the required improvement for each experience aspect across different target levels.

Our findings reveal several key patterns:

1. For both departments, kind reception and pain management consistently appear as priority areas across all improvement targets
2. The surgical department requires more focus on nursing care aspects, including fear/anxiety management by nurses
3. The medical department places greater emphasis on respect and dignity shown by doctors

Table 2: Summary of Required Improvements for Each Experience Aspect by Department

Experience Aspect	Surgical			Medical		
	1%	3%	5%	1%	3%	5%
Kind reception	0.15	0.15	0.15	0.12	0.15	0.15
Fear/anxiety (nurses)	0.09	0.15	0.15	-	-	0.15
Pain management	0.15	0.15	0.15	0.15	0.15	0.15
Respect (doctors)	-	0.15	0.15	-	0.15	0.15
Respect (nurses)	-	0.08	0.15	-	-	0.05
Involvement	-	-	0.15	-	-	0.15

4. To achieve higher improvement targets (4-5%), both departments need to address additional factors, including patient involvement
5. The model successfully identifies the minimal set of factors required for each improvement level, providing an efficient roadmap for quality improvement

These results align with the findings of [3], confirming that different departments require different improvement approaches, even though some core aspects (like pain management) are universally important.

4.3 Comparison with Previous Research

Our implemented model produces results that are highly consistent with those reported by [3]. The key similarities include:

- Identification of kind reception and pain management as universal priorities
- Greater importance of nursing care in surgical departments
- Significance of respect and dignity shown by doctors in medical departments
- Incremental addition of factors as the target improvement level increases

The consistency of these findings across different methodological approaches strengthens the validity of both our model and the original research.

5 Discussion

5.1 Key Findings

Our machine learning and optimization approach demonstrates that not all statistically significant determinants of satisfaction should be the primary focus of improvement actions. Instead, strategic selection through appropriate tools like our optimization model can guide informed managerial decisions with a clear focus on different healthcare settings.

The identification of kind reception and pain management as universal priorities across departments highlights the fundamental importance of these aspects to the patient experience, regardless of the clinical context. This finding aligns with previous research emphasizing the impact of first impressions [11] and effective pain management [12] on patient satisfaction.

The different priorities identified for surgical versus medical departments reflect their distinct patient populations and care requirements. The surgical department's emphasis on nursing care aligns with research by [13], who noted that surgical patients may have greater pain or recovery challenges requiring more nursing care. Similarly, the medical department's focus on respect and dignity from doctors reflects the generally older patient population with more chronic conditions, who may value the interpersonal aspects of physician care more highly.

5.2 Practical Implications

This research provides healthcare managers and practitioners with a practical, data-driven approach to prioritizing quality improvement actions. The model offers several advantages:

- **Efficient resource allocation:** By identifying the minimal set of factors needed for target improvements, the model helps healthcare organizations allocate limited resources effectively
- **Context-specific guidance:** The differentiation between surgical and medical departments provides tailored recommendations for different clinical settings
- **Scalable improvement strategy:** The model provides a roadmap for incremental improvements, allowing organizations to build on initial successes
- **Evidence-based decision-making:** The approach transforms patient-reported data into actionable insights, addressing challenges in data utilization noted by [14]

Healthcare organizations can implement this approach by:

1. Collecting patient experience data through standardized surveys
2. Applying the model to identify department-specific priority areas
3. Developing targeted quality improvement initiatives focused on these priorities
4. Monitoring changes in both specific experience items and overall satisfaction
5. Iteratively refining the approach based on results

5.3 Limitations

Our study has several limitations that should be considered:

- Use of synthetic data: While our synthetic data mirrors the characteristics described in the original research, validation with real patient survey data would strengthen the findings
- Simplified cost structure: The model assumes uniform costs for improving different aspects of care, which may not reflect reality
- Binary classification: For implementation simplicity, we converted the ordinal satisfaction scale to a binary outcome, potentially losing some nuance
- Limited context factors: The model does not account for facility-level characteristics that might influence both experience and satisfaction

5.4 Future Research

Several directions for future research emerge from this work:

1. Incorporation of cost structures into the optimization model to reflect varying difficulty in improving different aspects of care
2. Application of the model to other healthcare settings, such as outpatient care, emergency departments, or primary care
3. Exploration of temporal patterns through longitudinal analysis
4. Development of multi-level models that incorporate both patient-level and facility-level factors
5. Creation of interactive decision support tools for healthcare managers based on the model

6 Conclusions

This study presents a novel machine learning approach for optimizing healthcare user experience based on patient-reported data. By combining ordinal logistic regression with mathematical optimization, our model identifies the most efficient combination of experience factors to improve overall patient satisfaction in different healthcare settings.

The results demonstrate that targeted improvements in specific experiential aspects—such as kind reception, pain management, and respectful treatment—can lead to significant increases in patient satisfaction. Importantly, our approach recognizes the different priorities for surgical and medical departments, reflecting their distinct patient populations and care requirements.

This research provides healthcare managers with an evidence-based, resource-efficient framework for quality improvement initiatives that is directly informed by patient perspectives. By moving beyond simply collecting patient data to strategically analyzing and applying it, our approach supports the ongoing shift toward more patient-centered healthcare delivery.

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