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Enhancing Patient Experience Continuity Across Care Transitions: An NLP-Driven Approach to Understanding Free-Text Feedback

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Abstract: Background: Patient experience is a cornerstone of quality healthcare, yet continuity of care, particularly during transitions, remains a significant challenge. Traditional feedback mechanisms often lack the depth to capture nuanced patient perspectives on these critical junctures. Natural Language Processing (NLP) offers a scalable solution to analyze vast quantities of unstructured free-text feedback, providing rich insights into patient journeys.

Objective: This study aimed to leverage NLP and machine learning to analyze free-text patient feedback from diverse healthcare settings to identify key themes, sentiments, and specific pain points related to patient experience continuity during care transitions.

Methods: Over 69,000 free-text patient responses collected from various NHS settings (outpatient, inpatient, A&E, and maternity) were analyzed using NLP techniques, including sentiment analysis and trigram analysis. A Support Vector Machine (SVM) model was employed for theme classification, with its performance compared against five other machine learning models.

Results: The SVM model demonstrated superior classification accuracy, achieving 74.5% for outpatient feedback, 72.2% for inpatient, 71.5% for A&E, and 62.7% for maternity feedback. Sentiment analysis revealed that negative feedback predominantly centered on critical transition points, specifically discharge processes, information continuity, and follow-up care. Frequent negative trigrams identified across settings included “seeing different doctor,” “improve discharge process,” and “information aftercare lacking,” underscoring systemic issues in care handovers and communication.

Conclusion: This study demonstrates the viability and efficacy of using NLP and machine learning to process large-scale patient feedback, efficiently uncovering specific areas of dissatisfaction related to care transitions. The insights gained provide actionable intelligence for healthcare providers to design targeted quality improvement interventions, fostering enhanced communication, discharge planning, and inter-departmental coordination to improve patient experience continuity and advance patient-centered care.

Keywords: Natural Language Processing, Patient Experience, Care Transitions, Machine Learning, Sentiment Analysis, Quality Improvement, Healthcare.

Introduction: 1.1 Background and Significance of Patient Experience

The patient experience has emerged as a cornerstone of healthcare quality and a critical determinant of health outcomes. Beyond clinical effectiveness and safety, how patients perceive and interact with healthcare services significantly influences their satisfaction, adherence to treatment, and overall well-being [1, 3, 23]. In recent decades, there has been a global paradigm shift towards patient-centered care, emphasizing the importance of understanding and responding to individual patient needs, preferences, and values [21, 23]. This shift acknowledges that patients are active participants in their care journey, and their perspectives offer invaluable insights into the strengths and weaknesses of healthcare systems.

Traditionally, patient feedback has been collected through structured surveys, such as the Friends and Family Test in the NHS [2]. While these tools provide quantitative metrics and a broad overview of satisfaction, they often fall short in capturing the nuanced, contextual, and deeply personal aspects of the patient journey. Structured questionnaires, by their very nature, limit responses to predefined categories, potentially overlooking critical details and emotional undertones that truly reflect a patient's lived experience. This limitation creates a gap in understanding, hindering healthcare providers' ability to identify specific areas for improvement and to implement truly patient-centric interventions.

1.2 The Critical Role of Care Transitions

Continuity of care is a fundamental component of high-quality healthcare, ensuring that patients receive coordinated and uninterrupted services across different providers, settings, and time points [25]. However, care transitions—movements between healthcare settings, such levels of care, or different providers—represent inherently vulnerable periods for patients. These transitions, whether from inpatient to outpatient care, between primary and secondary care, or even within different departments of the same hospital, are fraught with potential risks. Research consistently demonstrates that a significant proportion of adverse events affecting patients occur after discharge from the hospital, often directly attributable to breakdowns in communication, information transfer, and coordination during these transitional phases [8, 9, 28]. Patients frequently report dissatisfaction stemming from inadequate discharge instructions, lack of clarity regarding follow-up appointments, and insufficient information about their ongoing care needs [26, 27]. For older adults and those with complex care needs, these transitions can be particularly challenging, leading to fragmented care and poorer outcomes [27, 28]. The absence of seamless continuity can undermine patient safety, reduce treatment adherence, and ultimately diminish the overall patient experience.

1.3 Emergence of Free-Text Feedback and Natural Language Processing (NLP)

In recognition of the limitations of structured feedback, there has been a growing appreciation for the value of unstructured, free-text comments provided by patients. These narratives, often collected through online platforms, comment cards, or direct feedback mechanisms, offer rich, authentic, and unsolicited insights into patient experiences [4, 5, 15]. They allow patients to express their concerns, praises, and suggestions in their own words, providing a depth of detail and emotional context that structured surveys cannot match. However, the sheer volume of such free-text data presents a significant analytical challenge. Manually reviewing and coding thousands, or even tens of thousands, of comments is an arduous, time-consuming, and resource-intensive process, often impractical for real-time quality improvement initiatives [4].

This analytical challenge has spurred the adoption of Natural Language Processing (NLP) – a subfield of artificial intelligence that enables computers to understand, interpret, and generate human language. NLP offers a powerful and scalable solution for automated analysis of large volumes of text data in healthcare [10, 11, 17, 19, 22]. By applying NLP techniques, healthcare organizations can efficiently extract meaningful information, identify recurring themes, and gauge sentiment from vast datasets of patient narratives, transforming raw text into actionable intelligence. This technological advancement holds the promise of moving beyond merely collecting data to actively using it for continuous improvement [1].

1.4 Research Gap and Study Objective

While NLP has been successfully applied to analyze general patient satisfaction and physician reviews in various healthcare contexts [14, 18, 20], there remains a critical need for its focused application on the specific domain of continuity of care across transitions. Despite the known vulnerabilities and patient dissatisfaction associated with these periods, a comprehensive, large-scale analysis of free-text feedback specifically targeting transitional care experiences using advanced NLP and machine learning techniques is less common. Understanding the precise language and recurring concerns patients express about handovers, discharge, and follow-up is crucial for designing effective interventions.

Therefore, the objective of this study was to leverage NLP and machine learning to analyze a large dataset of free-text patient feedback from diverse NHS settings. The primary goal was to identify key themes, sentiments, and specific pain points directly related to the continuity of patient experience during care transitions, thereby providing granular insights that can inform targeted quality improvement efforts.

1.5 Contribution and Structure of the Article

This article contributes significantly to the understanding of patient experience in care transitions by demonstrating the practical application and efficacy of NLP and machine learning on a large, real-world dataset. The findings offer actionable insights for healthcare providers seeking to enhance continuity of care, improve patient safety, and foster greater patient satisfaction. The remainder of this article is structured as follows: Section 2 details the methodological approach, including data collection, preprocessing, and the NLP and machine learning techniques employed. Section 3 presents the key results, including model performance and the identified pain points. Section 4 discusses the implications of these findings for quality improvement and the broader role of AI in patient-centered care, alongside study limitations and future research directions. Finally, Section 5 concludes the article by summarizing the study's main contributions.

METHODS

2.1 Study Design

This study employed a retrospective, quantitative design, utilizing advanced Natural Language Processing (NLP) and machine learning techniques to analyze existing free-text patient feedback. The approach focused on extracting themes, sentiments, and specific concerns related to patient experience, with a particular emphasis on identifying issues pertinent to continuity of care during transitions. This methodological choice allowed for the efficient processing of a large volume of unstructured data, providing a scalable and objective means of understanding patient perspectives.

2.2 Data Source and Collection

The dataset for this study comprised over 69,000 free-text responses from patient feedback collected across various National Health Service (NHS) settings within the United Kingdom. These responses originated from diverse points of care, including outpatient clinics, inpatient wards, Accident & Emergency (A&E) departments, and maternity services. The feedback was collected through established NHS mechanisms designed to gather patient comments, ensuring a broad representation of experiences across different care pathways. To protect patient privacy and comply with ethical guidelines, all free-text responses were rigorously anonymized prior to their inclusion in the study. This anonymization process involved the removal of any personally identifiable information, ensuring that the analysis focused solely on the content of the feedback without compromising patient confidentiality. Ethical approval for the use of this anonymized, aggregated data was obtained from the relevant institutional review boards.

2.3 Data Preprocessing

Before applying NLP and machine learning algorithms, the raw free-text data underwent a series of essential preprocessing steps to ensure its quality and suitability for analysis. These steps are crucial for transforming unstructured text into a format that computational models can effectively interpret.

1. Tokenization: The initial step involved tokenizing the text, breaking down each free-text response into individual words or phrases (tokens). This process converts continuous text into discrete units that can be processed.

2. Stop-word Removal: Common words that carry little semantic meaning (e.g., "the," "a," "is," "and") were identified and removed. These "stop words" are pervasive in natural language but often add noise rather than valuable information for thematic or sentiment analysis.

3. Stemming/Lemmatization: To reduce words to their base or root form, either stemming or lemmatization was applied. Stemming involves removing suffixes (e.g., "running" becomes "run"), while lemmatization reduces words to their dictionary form (e.g., "better" becomes "good"). This step helps in standardizing vocabulary and reducing the dimensionality of the data, ensuring that variations of the same word are treated as a single entity.

4. Normalization: This involved converting all text to lowercase and handling punctuation, special characters, and numerical digits. This ensures consistency and prevents the same word from being treated as different entities due to variations in capitalization or surrounding characters.

5. Noise Reduction: Irrelevant information, such as repetitive phrases, non-alphanumeric characters, or very short comments lacking substantive content, were identified and filtered out to improve the signal-to-noise ratio in the dataset.

2.4 Natural Language Processing Techniques

Two primary NLP techniques were employed to extract meaningful insights from the preprocessed free-text data: sentiment analysis and trigram analysis.

1. Sentiment Analysis: This technique was used to automatically determine the emotional tone or polarity of each patient comment. Each response was classified into one of three categories: positive, negative, or neutral. The sentiment analysis model was trained on a

subset of manually labeled data to learn the linguistic patterns associated with different sentiments in a healthcare context. This allowed for a large-scale, automated assessment of patient satisfaction and dissatisfaction across various aspects of care. The output of this analysis provided a quantitative measure of overall patient sentiment in relation to different care experiences, including transitions.

2. Trigram Analysis: To uncover common topics and specific concerns expressed by patients, trigram analysis was performed. A trigram is a sequence of three consecutive words in a text. By identifying frequently co-occurring trigrams, especially those associated with negative sentiment, the study could pinpoint specific issues, actions, or experiences that patients consistently highlighted. This method is particularly effective in revealing phrases that represent recurring problems or areas of dissatisfaction, such as "seeing different doctor" or "improve discharge process." This provided a more granular understanding of patient feedback compared to single-word analysis.

2.5 Machine Learning for Theme Classification

To further categorize and understand the underlying themes within the patient feedback, machine learning models were trained to classify comments into predefined categories, particularly those related to care transitions (e.g., discharge, information flow, follow-up care).

1. Model Selection: Six different machine learning models were evaluated for their ability to accurately classify the patient feedback themes. These models included, but were not limited to, Logistic Regression, Naive Bayes, Decision Trees, Random Forests, Gradient Boosting, and Support Vector Machine (SVM). After rigorous comparative testing, the Support Vector Machine (SVM) model consistently demonstrated the highest accuracy across the diverse datasets, leading to its selection as the primary classification model for this study. SVMs are particularly well-suited for text classification tasks due to their effectiveness in high-dimensional spaces and their ability to handle complex, non-linear relationships within the data.

2. Training and Validation: The preprocessed dataset was split into three distinct sets: a training set (70%), a validation set (15%), and a test set (15%). The training set was used to teach the SVM model the patterns and relationships between text features and their corresponding themes. The validation set was used for hyperparameter tuning and model optimization, ensuring that the model generalized well to unseen data.

3. Feature Engineering: To enable the machine learning model to process text data, the textual comments were converted into numerical features. This was primarily achieved using techniques such as Term Frequency-Inverse Document Frequency (TF-IDF), which assigns weights to words based on their frequency in a document relative to their frequency across the entire corpus. This method captures the importance of words within a document and across the dataset, providing a robust numerical representation for the SVM model.

4. Classification Task: The SVM model was trained to perform a multi-class classification task. Each patient comment was classified into one or more predefined themes, which were carefully curated based on common issues in patient experience and, crucially, those specifically related to care transitions. Examples of such themes included "discharge process," "communication with staff," "information provision," "follow-up arrangements," and "coordination of care." This allowed for a systematic categorization of feedback, enabling a quantitative analysis of where specific issues arose.

2.6 Performance Metrics

The primary metric used to evaluate the performance of the machine learning models, particularly the selected SVM, was accuracy. Accuracy measures the proportion of correctly classified instances (patient comments) out of the total number of instances. While other metrics like precision, recall, and F1-score were also considered during model selection, accuracy provided a clear and easily interpretable measure of the model's overall effectiveness in identifying the correct themes within the patient feedback.

2.7 Software and Tools

The data preprocessing, NLP techniques, and machine learning model training were implemented using standard Python libraries. Specific libraries utilized included NLTK (Natural Language Toolkit) for text preprocessing and sentiment analysis, scikit-learn for machine learning model implementation (including SVM), and pandas for data manipulation and analysis.

RESULTS

3.1 Overview of Patient Feedback Data

The analysis encompassed a substantial dataset of over 69,000 free-text patient responses collected from various NHS settings. The distribution of feedback across these settings was broadly reflective of patient flow, with a significant proportion originating from outpatient and inpatient services, followed by A&E and maternity departments. Initial sentiment analysis of the entire dataset revealed a mixed but generally positive overall sentiment, which is common in patient feedback systems where patients often provide positive comments or choose not to comment unless there is a significant experience. However, a crucial aspect of this study was to delve deeper into the negative sentiments, particularly those associated with specific points of care and transitions.

3.2 Machine Learning Model Performance

The evaluation of six different machine learning models for theme classification demonstrated the superior performance of the Support Vector Machine (SVM) model. The SVM consistently outperformed the other tested models (including Logistic Regression, Naive Bayes, Decision Trees, Random Forests, and Gradient Boosting) in accurately categorizing free-text comments into predefined themes related to patient experience and care transitions.

The accuracy scores achieved by the SVM model across different NHS settings were as follows:

Setting	SVM Model Accuracy (%)
Outpatient	74.5
Inpatient	72.2
A&E	71.5
Maternity	62.7

These accuracy scores, particularly the high performance in outpatient, inpatient, and A&E settings, validate the use of SVMs in healthcare NLP applications for classifying patient feedback themes. While the accuracy for maternity feedback was slightly lower, it still represented a significant improvement over baseline models and provided valuable insights. The consistent performance across diverse settings underscores the robustness and generalizability of the SVM approach for this type of textual analysis.

3.3 Identification of Critical Pain Points in Care Transitions

A central finding of this study was the clear identification of transitions of care as critical pain points within the patient journey, frequently associated with negative sentiments. Quantitative and qualitative evidence derived from the sentiment and thematic analysis consistently showed that patient dissatisfaction often centered around three key aspects of transitional care: discharge processes, information continuity, and follow-up care.

This pattern was particularly pronounced in inpatient and A&E settings, where the complexity and urgency of care often lead to more abrupt transitions. Patients frequently expressed frustration regarding:

- Discharge: Comments highlighted issues such as rushed discharges, lack of clear instructions, feeling unprepared to leave, and insufficient support plans for home.
- Information Continuity: A recurring concern was the perceived lack of seamless information transfer between different healthcare professionals or departments. Patients often felt that their medical history, current condition, or treatment plan was not adequately communicated to subsequent care providers.
- Follow-up Care: Significant negative feedback related to the clarity and timeliness of follow-up appointments, prescriptions, and ongoing care instructions. Patients expressed anxiety and confusion when unsure about the next steps in their recovery or management.

These findings directly align with existing literature on the vulnerabilities of care transitions, reinforcing the notion that these periods are indeed high-risk for patient dissatisfaction and potential adverse events [8, 9, 28].

3.4 Common System-Wide Concerns from Trigram Analysis

The trigram analysis provided a more granular understanding of the specific language patients used to express their negative experiences, revealing shared system-wide concerns related to care handovers and communication. The most frequently occurring negative trigrams included:

- “seeing different doctor”: This trigram consistently appeared in negative feedback, highlighting patient frustration with a lack of relational continuity. Patients often value seeing the same doctor or a consistent team, and the frequent change of personnel during transitions or subsequent visits was a significant source of dissatisfaction. This suggests a breakdown in relational continuity, where patients feel they have to repeatedly explain their history or that their care is not being managed by a consistent, familiar professional.

● "improve discharge process": This phrase directly points to the critical need for better discharge planning and execution. It encapsulates concerns about insufficient information, hurried explanations, lack of coordination with community services, and patients feeling unprepared for self-care post-discharge. This trigram was prevalent across inpatient and A&E settings, underscoring the systemic nature of discharge-related issues.

● "information aftercare lacking": This trigram directly addresses informational continuity, indicating that patients often feel inadequately informed about their care once they leave a particular setting. This includes details about medication, warning signs, whom to contact if problems arise, and the overall plan for their recovery or ongoing management. The recurrence of this phrase emphasizes a significant communication gap in the post-transition phase.

These specific trigrams, derived from the automated analysis of thousands of comments, provide concrete linguistic evidence of consistent dissatisfaction with care handovers and communication across the NHS settings studied. They offer precise targets for quality improvement initiatives, moving beyond general complaints to specific, actionable areas.

DISCUSSION

4.1 Interpretation of Findings

This study unequivocally demonstrates that Natural Language Processing (NLP) and machine learning are powerful tools for processing large-scale patient feedback, offering significant scalability and efficiency compared to traditional manual methods [4, 17, 19, 22]. The ability to analyze over 69,000 free-text responses from diverse NHS settings highlights the potential of these technologies to transform how healthcare organizations capture and utilize patient voices. The high accuracy achieved by the Support Vector Machine (SVM) model in classifying feedback themes (ranging from 62.7% to 74.5% across different settings) further validates its utility and reliability in complex healthcare NLP applications. This level of accuracy indicates that automated systems can reliably identify and categorize patient concerns, providing a robust foundation for data-driven decision-making.

The most salient finding is the consistent identification of transitions of care as critical pain points for patients. The concentration of negative sentiments around discharge processes, information continuity, and follow-up care, particularly in inpatient and A&E settings, reinforces existing literature on the vulnerabilities inherent in these phases. Breakdowns in continuity during transitions are well-documented contributors to adverse events, readmissions, and patient dissatisfaction [8, 9, 28]. Our findings provide empirical evidence from the patient's perspective, using their own words to highlight where these cracks appear.

The specific negative trigrams identified—"seeing different doctor," "improve discharge process," and "information aftercare lacking"—offer granular insights into the nature of these continuity challenges. "Seeing different doctor" speaks to a deficit in relational continuity, where the patient's trust and understanding built with one provider are disrupted by a change in personnel [24]. This can lead to patients feeling unheard or requiring them to repeatedly recount their medical history. "Improve discharge process" directly targets issues in management continuity, encompassing the coordination of services, planning for post-discharge needs, and ensuring patients feel prepared and supported upon leaving a care setting [26]. Finally, "information aftercare lacking" clearly points to a critical failure in informational continuity, where essential details about medication, symptoms to monitor, and subsequent steps in care are not adequately communicated [25]. These findings underscore that patient experience is profoundly impacted by the seamless flow of information and coordination of care across the entire healthcare continuum.

4.2 Implications for Quality Improvement (QI)

The insights derived from this study offer direct and actionable intelligence for healthcare providers to design targeted quality improvement initiatives [16]. By pinpointing the specific areas of dissatisfaction related to care transitions, organizations can move beyond generic interventions to implement highly focused changes. For instance:

● Enhancing Communication Protocols: The frequent mention of "information aftercare lacking" highlights the need for standardized, clear, and comprehensive discharge instructions. This could involve using plain language, providing written and verbal instructions, and incorporating teach-back methods to ensure patient understanding. Furthermore, improving inter-provider communication channels, perhaps through shared electronic health records or structured handoff protocols, could address the "seeing different doctor" concern by ensuring all relevant information is accessible to every team member.

● Improving Discharge Planning: The recurring demand to "improve discharge process" calls for a more patient-centered approach to discharge. This involves earlier discharge planning, involving patients and their families in the process, coordinating with community services (e.g., home care, social services) before discharge, and ensuring follow-up appointments are scheduled and communicated clearly.

● Fostering Better Coordination Across Departments: The overarching theme of continuity issues suggests a need for enhanced coordination between different hospital departments (e.g., A&E to inpatient, inpatient to outpatient) and between hospital and primary care settings. This could involve integrated care pathways, shared care plans, and dedicated transition navigators to guide patients through complex care journeys.

These targeted interventions, directly informed by patient feedback, are crucial as they address factors directly linked to patient satisfaction, safety, and ultimately, better health outcomes. By systematically addressing these pain points, healthcare systems can reduce adverse events and improve the overall quality of care.

4.3 The Role of Real-Time Analytics in Healthcare

The methodology employed in this study demonstrates that NLP-driven insights can be generated quickly and on a large scale. This capability is transformative, enabling dynamic monitoring of patient experience and facilitating an immediate response to emerging issues. Unlike traditional feedback cycles that can be slow and retrospective, automated analysis allows healthcare organizations to identify trends, spikes in negative sentiment, or new pain points in near real-time. This agility supports a proactive approach to quality improvement, allowing for rapid adjustments to care delivery models or communication strategies. For example, if a sudden increase in "information aftercare lacking" comments is detected in a specific ward, interventions can be deployed swiftly, rather than waiting for quarterly survey results. This fosters a truly responsive healthcare system that can adapt to patient needs as they evolve.

4.4 Viability of AI in Patient-Centered Care

This study unequivocally showcases how integrating Artificial Intelligence (AI), specifically NLP and machine learning, into healthcare feedback systems supports transparency, responsiveness, and service design rooted in lived patient experiences. By automating the analysis of vast quantities of unstructured data, AI empowers healthcare providers to truly listen to the "voice of the patient" at an unprecedented scale. This moves beyond merely collecting data to actively using it to inform strategic decisions and operational changes. Positioning AI as a facilitator for truly patient-centered care means leveraging technology not to replace human interaction, but to enhance the ability of healthcare systems to understand, empathize with, and respond to the individual needs of each patient. It enables a continuous feedback loop that drives iterative improvements in care delivery, making healthcare services more accountable and aligned with patient expectations.

4.5 Limitations

Despite the significant contributions of this study, several limitations warrant consideration. Firstly, the reliance solely on free-text data, while rich in detail, inherently carries potential biases. Patients who choose to provide free-text comments may represent a specific demographic or have particularly strong positive or negative experiences, potentially not reflecting the full spectrum of patient opinions. Furthermore, free-text comments can sometimes lack demographic context, making it challenging to understand if certain issues disproportionately affect particular patient groups.

Secondly, while the dataset of over 69,000 responses is substantial, the generalizability of findings is primarily limited to NHS settings within the UK. Healthcare systems, cultural contexts, and patient expectations can vary significantly across different countries, meaning the specific pain points identified may not be universally applicable without further validation.

Thirdly, interpreting nuanced language, sarcasm, or highly contextual comments remains a challenge for even advanced NLP models. While the SVM model achieved high accuracy, there is always a degree of inherent ambiguity in human language that automated systems may misinterpret. This necessitates the need for human oversight in validating NLP outputs, especially when using the insights for critical decision-making.

Finally, while the study identified critical pain points, it did not directly measure the impact of addressing these issues on patient outcomes or safety. Future research would benefit from linking NLP-derived insights to measurable improvements in clinical outcomes.

4.6 Future Research

Building upon the findings of this study, several avenues for future research emerge. Firstly, incorporating other data sources, such as electronic health records (EHRs) or administrative data, alongside free-text feedback could provide a more holistic view of the patient journey and allow for correlation between expressed experiences and clinical outcomes. Secondly, longitudinal studies tracking patient feedback over time would enable a deeper understanding of how interventions impact patient experience and continuity of care over extended periods.

Thirdly, real-time intervention testing, where specific quality improvement initiatives are deployed based on NLP-derived insights and their effectiveness is immediately monitored through subsequent patient feedback, would provide valuable evidence of impact. Exploring more advanced NLP models, such as deep learning architectures (e.g., transformer models), could potentially yield even higher accuracy and more nuanced understanding of complex patient narratives. Finally, conducting cross-cultural comparisons of patient feedback on care transitions would provide insights into universal challenges versus context-specific issues, informing global best practices in patient-centered care.

CONCLUSION

This study has successfully demonstrated the profound utility of Natural Language Processing and machine learning in analyzing large volumes of free-text patient feedback to effectively identify critical pain points in care transitions. By systematically processing over 69,000 patient comments, we uncovered consistent themes of dissatisfaction related to discharge processes, information continuity, and follow-up care, particularly in inpatient and A&E settings. The high accuracy of the SVM model validates the scalability and efficiency of this automated approach, offering a significant improvement over manual analysis methods. The specific negative trigrams identified, such as “seeing different doctor,” “improve discharge process,” and “information aftercare lacking,” provide concrete, actionable insights for healthcare providers. This research underscores the transformative value of NLP and machine learning in enhancing patient experience monitoring, enabling real-time analytics, and supporting agile responses in healthcare. Ultimately, the insights derived from this study have the potential to drive meaningful, targeted improvements in healthcare continuity and advance the delivery of truly patient-centered care.

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