# ICU Patient Report

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## Introduction

The ICU director has tasked our team with enhancing patient care while controlling costs, with particular emphasis on reducing length of stay and lowering mortality rates. To support this objective, we analyzed several years of electronic medical records using statistically valid methods ($p < 0.05$, 95% confidence) to identify patient variables that meaningfully influence these outcomes. Our models revealed two factors with significant impact: the number of medications a patient receives and the patient's age.

This report interprets these findings for organizational stakeholders and examines how they could inform practical decision-support strategies for example, systems that help clinicians optimize prescribing practices or risk-identification tools that flag higher-risk patients based on age. It also addresses the practical, ethical, and operational considerations the organization must weigh when implementing such data-driven interventions in a clinical environment.

## Section 0: Executive Summary Presentation

This video briefing presents the executive summary of the project, outlining the organizational context and the objectives driving the data science initiative. It highlights the analytical approach and methodology used to conduct the study, followed by a clear presentation of the key findings. The briefing concludes with actionable recommendations designed to guide stakeholders in applying these insights to organizational decision-making.

Executive summary video

## Section 1: Organizational Interpretation of results

### Section 1.1: Translating Technical Results to Organizational impact

Our analysis demonstrates that age and the number of medications administered are statistically significant predictors of patient outcomes. At a 95% confidence level ($p < 0.05$), we can conclude that both variables affect mortality rates, and that the number of medications also influences length of stay. These findings provide a robust evidence base for guiding ICU practices and organizational decision-making.

With statistically validated insights into factors driving patient mortality and length of stay, the ICU department is positioned to implement procedural changes and supportive technologies that directly improve care delivery.

Patients prescribed a higher number of medications are associated with longer hospital stays and increased mortality risk. By flagging these patients early, caregivers can prioritize medication management, conduct pharmacy reviews, and coordinate multidisciplinary care. This proactive approach has the potential to reduce length of stay and improve patient outcomes.

Older patients consistently demonstrate higher mortality risk. Implementing age-based risk stratification enables caregivers to monitor these patients more closely, ensuring timely interventions and reducing preventable complications.

Identifying patients at elevated risk of prolonged stays or mortality allows the hospital to optimize staffing, allocate ICU beds more effectively, and schedule interventions proactively. Over time, this can translate into shorter average length of stay, lower complication rates, improved patient safety, and reduced costs associated with extended hospitalization.

It is important to note that the model does not include patients under 21 years old due to HIPAA restrictions. As a result, confidence in age-related findings does not extend to younger populations. However, the model performs strongly for patients with high medication counts, where statistical significance is consistently observed.

Mortality bracelet program: Introducing a mortality risk bracelet could improve patient care and enhance the hospital's reputation by visibly reducing mortality rates. While implementation carries a modest cost, the lives saved and reputational benefits far outweigh the investment.

Medication recommendation system: Developing a prescription optimization system will require pharmacist input to catalog drug combinations and their therapeutic effects. During development,

a manual process can be adopted in which pharmacists review prescriptions and advise physicians on alternatives. In parallel, software engineers can integrate a recommendation engine into the hospital's ERP system. Once implemented, the system will automatically flag incompatible prescriptions, suggest alternatives, and highlight the most effective drug regimens. Although this initiative requires upfront investment in pharmacist time, engineering resources, and training, it is expected to reduce both length of stay and mortality by ensuring safer, more effective prescribing practices.

Section 1.2: Insights and Recommendations

The model reveals two key predictors of patient outcomes in the ICU:

Medication burden: Patients receiving a higher number of prescriptions tend to experience both longer ICU stays and higher mortality rates.

Age: Older patients consistently show higher mortality risk compared to younger patients when admitted to the ICU.

An unexpected finding was that the number of diagnoses did not correlate with either length of stay or mortality. Intuitively, one might expect that more diagnoses would prolong recovery. However, many diagnoses can stem from a single underlying etiology, meaning that multiple issues may be resolved by a single treatment. For example, a patient presenting with internal bleeding, diarrhea, and lightheadedness could have scurvy—where the resolution is simply correcting a vitamin C deficiency. This highlights the importance of focusing on root causes rather than diagnosis counts.

Mortality Risk Bracelet System Introduce a color-coded bracelet system to stratify patients by mortality risk at the point of hospital admission.

Cold colors (e.g., dark blue) would indicate low risk.

Hot colors (e.g., bright red) would indicate high risk. For example, a 21-year-old patient might receive a dark blue bracelet, while an 80-year-old patient would receive a bright red one. These

bracelets would help ICU staff quickly identify high-priority patients, enabling more frequent monitoring and targeted interventions. This system would improve care prioritization and ensure additional coverage for patients most at risk.

Medication Review and ERP Integration Implement a secondary review process for prescriptions, conducted by pharmacists in collaboration with physicians.

Pharmacists would evaluate administration timing, recovery implications, drug strength relative to alternatives, and compatibility with other medications.

Physicians would retain final prescribing authority, but the additional review provides a safeguard against adverse drug interactions. Longer-term, this process should be integrated into the hospital's ERP system. A dropdown interface could automatically flag incompatible prescriptions, block unsafe combinations, and suggest safer alternatives. Developing this feature would require collaboration between pharmacists and software engineers to build a comprehensive compatibility database. While resource-intensive, this system would reduce medication-related risks, shorten ICU stays, and lower mortality rates.

Section 1.3 Risk Assessment and mitigation strategies

A key limitation of the model arises when patients cannot effectively articulate their symptoms or medical history. For example, patients with limited English proficiency (ESL) may struggle to communicate allergies such as a sulfa sensitivity. If hospital staff are unaware of these critical details, inappropriate treatments could be administered, potentially harming the patient. Similarly, miscommunication or misunderstanding during intake can lead to incorrect diagnoses, resulting in inappropriate prescriptions and delayed recovery.

The quality of data is closely tied to the timeliness of prescription reviews. While the planned recommendation system should streamline medication reconciliation, delays are likely during initial implementation. Extended review times between physicians and pharmacists could slow patient service delivery, negatively affecting care outcomes until the system is fully optimized.

Procedural changes carry inherent organizational risks. One concern is the tradeoff between medication strength and versatility. For instance, a slightly less potent drug may be chosen

because it addresses multiple conditions simultaneously, whereas a stronger alternative might be more effective but less flexible. While such tradeoffs may appear minor, even a small percentage difference in efficacy can translate into lives lost.

Another organizational risk involves hospital reputation. If competitors prescribe stronger, single-use medications while our hospital opts for broader but weaker alternatives, stakeholders may perceive that efficiency (e.g., reducing ICU days) is prioritized over delivering the strongest possible care. This perception could undermine trust and damage the hospital's reputation.

The model excludes patients under 21 due to HIPAA restrictions, leaving younger populations unrepresented. As a result, recommendations derived from the model may not apply to adolescents or pediatric patients and could inadvertently cause harm if applied without adjustment. Ethical oversight is required to ensure that interventions are not generalized beyond the population studied.

Mitigation Approaches

Standardized Multilingual Intake Forms

Implement kiosks with language options to capture patient symptoms and medical history at admission.

If patients are unable to complete forms, administrators will collect information once the patient is conscious.

This process ensures accurate documentation and reduces risks associated with translation errors or incomplete records.

Pharmacist Review and Kanban Workflow

Establish a structured review process where physicians submit prescriptions to pharmacists via a kanban-style system.

Each prescription moves through clear stages (e.g., "submitted," "reviewed," "completed"), ensuring accountability and transparency.

Physicians can set due times; if pharmacists cannot review within the window, the physician's prescription proceeds by default.

Decision authority remains weighted toward physicians (80%), but pharmacists retain the ability to document concerns and reject unsafe prescriptions.

This dual-review process provides an additional safeguard, ensuring that the most appropriate medication is prescribed.

ERP-Integrated Recommendation System

Long-term, integrate the review process into the hospital's ERP system.

The system will automatically flag incompatible prescriptions, block unsafe combinations, and suggest alternatives.

Collaboration between pharmacists and software engineers will be required to build a comprehensive compatibility database.

While resource-intensive, this system will reduce medication-related risks, improve patient safety, and enhance operational efficiency.

Section 2: Project Review and reflection

2.1 Project Retrospective

After the initial assignment, the project began to flow more smoothly as I developed a rhythm. One success was creating joined datasets to analyze key variables. My SQL training proved invaluable here, helping me select the appropriate joins and write correct syntax. Another positive outcome was the systematic removal of variables that did not contribute to the project's objectives. At first, the sheer volume of data felt overwhelming. By reducing variables early, I avoided unnecessary tangents and focused on analyses that provided meaningful business value. This streamlined approach ultimately improved the quality and efficiency of the analysis.

The first major challenge was time management. The initial deadline coincided with other coursework, creating significant pressure. While the short-term solution was simply working longer hours, I mitigated future conflicts by planning ahead and completing assignments for other classes early.

A second challenge arose during exploratory data analysis. Joining multiple datasets created an unmanageable number of rows, with redundancy and duplication making analysis impractical. To resolve this, I restructured the data: instead of tracking each individual prescription, I aggregated them into a single variable representing the total number of prescriptions per patient. This adjustment reduced dataset size, eliminated duplication, and enabled meaningful analysis.

In hindsight, I wish I had invested more time in the planning phase, particularly in understanding the variables and their relationships. While the project successfully identified age and number of drugs administered as significant predictors, these variables present challenges for implementation. Age, for example, cannot be controlled, though it can inform risk stratification and care prioritization. The number of drugs administered raises further questions about prescribing practices and patient management. Earlier feature engineering and deeper exploration of variable interactions might have revealed additional trends or correlations, strengthening the analysis and recommendations.

The CRISP-DM framework provided a helpful structure for my first data science project, guiding expectations and offering a clear process. However, the non-linear nature of CRISP-DM conflicted with the linear course timeline. Hard deadlines meant that once reports were submitted, earlier work could not be revisited, limiting the iterative benefits of the framework.

Reflecting on time spent:

Exploratory Data Analysis (EDA): ~50% Much of my effort went into determining which data aligned with the project's objective of reducing ICU length of stay and mortality. This phase felt like assembling pieces of a single puzzle from a box containing multiple puzzles.

Data Cleaning and Modeling: ~35% After initial variable selection, I conducted deeper cleaning to handle incomplete data and transform variables for analysis. This preparation enabled a smoother modeling phase with minimal issues.

Recommendations and Other Tasks: ~15% A significant portion of this time was devoted to developing actionable recommendations for the hospital. Given the ICU department's limited history with data analysis, I deemed a recommender system involving pharmacist review to be a viable solution. Although I initially struggled to justify the recommendation, iterative refinement allowed me to address ethical concerns and propose safeguards to reduce associated risks.

## 2.2 Lesson learned and future applications

This project strengthened my ability to select meaningful data and clean it efficiently, which improved both my understanding of the dataset and my ability to explain analyses in alignment with project objectives. I also gained valuable experience in writing README files and building a structured data repository. Prior to this project, I understood the importance of storing data in a clean environment but lacked knowledge of standard practices. Developing repositories and documentation taught me industry norms for transparency and reproducibility.

A major area of growth was reproducibility in data cleaning. Initially, I struggled with cleaning data in Excel while ensuring the steps could be replicated. This challenge pushed me to transition fully into Jupyter Notebooks, where I learned to script reproducible workflows, automate folder creation, and export datasets systematically. This shift not only improved efficiency but also ensured that my work could be replicated and audited.

The project underscored the importance of time management. Early in the semester, overlapping deadlines across multiple courses created significant strain. By prioritizing this assignment and planning ahead for subsequent tasks, I avoided similar conflicts later.

I also learned the critical role of the project's early stages. Compared to data cleaning and variable derivation, the actual analysis was relatively straightforward. Data cleaning consumed the majority of my time because it required careful thought about variable selection and modeling strategy. Exploratory Data Analysis (EDA) revealed surface-level trends, but once transformations began, the complexity increased, demanding deliberate planning to maintain project coherence.

Working with healthcare data highlighted the complexity of the industry and the need to consider multiple perspectives business, medical professionals, and patients. Unlike standard optimization projects, healthcare decisions cannot be made solely on statistical significance.

For example, the model revealed that the number of drugs administered strongly correlates with higher mortality and longer ICU stays. While this might suggest reducing prescriptions, such an action would be clinically inappropriate. Some medications cannot be administered together

without harmful side effects, and others may be prescribed to improve patient comfort even if they extend length of stay. Hospitals often prioritize patient well-being over efficiency, accepting longer stays to ensure recovery is less painful. This reinforced the importance of domain knowledge and ethical considerations when translating data insights into practice.

The project improved my proficiency with label encoding, which is essential for standardizing categorical variables and enabling effective analysis. I also identified future areas for growth:

XGBoost: A powerful library for regression and classification that offers speed and automatic handling of missing data. Its computational efficiency makes it an attractive option for future projects.

Plotly: An interactive visualization library that allows zooming and dynamic exploration of plots. While Seaborn and Matplotlib provided a strong foundation, Plotly offers opportunities to expand my visualization capabilities and engage stakeholders more effectively.

This project, conducted with the MIMIC-IV dataset, provided invaluable experience in healthcare analytics and compliance requirements. Building on this foundation, I am currently working on a diabetes-focused project to identify predictors of high-risk patients.

A key takeaway is the importance of encoding categorical variables properly. Age bins proved difficult to analyze and visualize, as each age was treated as a separate category. Converting age into categorical or binary features improved interpretability. Similarly, encoding gender as binary (e.g., female = 0, male = 1) simplified analysis and enabled more robust modeling. These lessons will guide my approach in future healthcare projects, ensuring cleaner data structures and more actionable insights.

Conclusion:

Based on the data analysis, two variables emerged as critical predictors of patient outcomes in the ICU: the number of prescribed medications and patient age. Addressing these factors can meaningfully reduce both length of stay and mortality rates.

To mitigate risks associated with polypharmacy, I recommend implementing a pharmacist review of all prescriptions prior to administration. Over time, this process should be integrated into the

hospital's ERP system, enabling automated prescription recommendations tailored to each patient's condition. Such a system would help ensure medication compatibility, reduce adverse interactions, and optimize treatment plans.

In addition, I propose introducing a color-coded mortality risk bracelet system based on patient age. Cold colors would indicate lower risk, while hot colors would signify higher risk. These bracelets would allow ICU staff to quickly identify patients requiring closer monitoring and prioritize care accordingly.