**Characterizing 30-Day All-Cause ICU Readmissions in Pregnant Patients**

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## Introduction

Health status during pregnancy has significant implications for maternal and child health, it's an important consideration for health systems. With a high maternal mortality rate in the US (22.3 deaths per 100,000 live births in 2022), factors like the rate of postpartum readmission contribute to the maternal mortality rate making it a crucial focus in healthcare[1,2]. This project aims to characterize the rate and causes of 30-day all-cause ICU readmissions among pregnant women and compare them to women of childbearing age in general. By identifying and understanding readmission drivers, our project can contribute to improving maternal healthcare and thus women's access to healthcare which can create better health outcomes across society.

This project aims to utilise data from the MIMIC-IV dataset to identify the readmission rates of pregnant and non-pregnant women. Our project aims to explore the critical issue of maternal health, focusing on how pregnancy impacts health outcomes, particularly readmission rates and DRG distributions. Given the rising concerns over maternal health, especially when the U.S., lags behind other peer nations in maternal health outcomes, this is a significantly important area of research[3]. Characterization of postpartum hospital readmissions within the first days after delivery hospitalization discharge could help to identify patients who need additional preparedness for discharge[4].

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[1] Firouzbakht, M., Nikbakht, H., & Omidvar, S. (2024). Risk factors for postpartum readmission: a prediction model in Iranian pregnant women. *BMC Pregnancy and Childbirth*, *24*(1), 466.
[2] Girsen, A. I., Leonard, S. A., Butwick, A. J., Joudi, N., Carmichael, S. L., & Gibbs, R. S. (2022). Early postpartum readmissions: identifying risk factors at birth hospitalization. *AJOG Global Reports*, *2*(4), 100094.
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## Methods

To investigate pregnant women in the MIMIC-IV dataset, we first had to define our pregnant women subset. We decided to define a patient as being pregnant if she either had a pregnancy-related ICD code, or a positive pregnancy test. MIMIC-IV includes both ICD-10 and ICD-9 codes, so the 'd_icd_diagnoses' table was filtered by ICD codes starting with Z34, Z36, Z37, Z39 and Z3A[5] (ICD-10 pregnancy-related codes) using the SQL LIKE operator in the WHERE clause, and ICD-9 pregnancy-related codes were filtered using the SQL BETWEEN operator for codes 630-679[6].

We joined the 'labitems' table with 'labevents' to filter all lab results by the 'itemid' associated with HCG lab tests, which measures whether human chorionic gonadotropin (hCG) is present in blood or urine, an indicator for pregnancy.[7] There are 2 types of HCG test: blood vs. urine. Through joining, we noticed that only urine tests were administered in the data set. As the 'value' column had a lot of null entries, we also used the 'comments' column to determine the results of the urine tests for pregnancy, visualized below in **Figure 1**. We utilized SQL's CASE-statement to classify a result as positive, negative or uncertain based on the first letters of the 'comments' field (e.g., WHEN comments LIKE 'POS%' THEN 'POS'). Finally, we joined our admissions, patients and diagnoses_icd tables with the filtered ICD codes and HCG results to categorize patients as either pregnant (if they had a corresponding ICD code or a positive HCG result) or not pregnant.

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[5] AAPC. (n.d.). *ICD-10 codes: Z00-Z99/Z30-Z3A*. Retrieved December 12, 2024, from https://www.aapc.com/codes/icd-10-codes-range/Z00-Z99/Z30-Z3A/
[6] https://cdn-links.lww.com/permalink/wnl/a/wnl_2018_08_24_houtchens_1_sdc1.pdf
[7] Mount Sinai Health System. (n.d.). *HCG blood test: Quantitative*. Retrieved December 12, 2024, from https://www.mountsinai.org/health-library/tests/hcg-blood-test-quantitative

| Row | comments | f0_ |
|---|---|---|
| 1 | FOR QUANTITATION OF POSITIVES, SEND SERUM FOR HCG. | 6804 |
| 2 | POSITIVE*.  FOR QUANTITATION OF POSITIVES, SEND SERUM FOR HCG. | 734 |
| 3 | POSITIVE.  FOR QUANTITATION OF POSITIVES, SEND SERUM FOR HCG. | 1882 |
| 4 | ___ | 407 |
| 5 | POS.  FOR QUANTITATION OF POSITIVES, SEND SERUM FOR HCG. | 85 |
| 6 | NEGATIVE - Level less than 10 miu/ml.  FOR QUANTITATION OF POSITIVES, SEND SERUM FOR HCG. | 12 |
| 7 | NEGATIVE.  FOR QUANTITATION OF POSITIVES, SEND SERUM FOR HCG. | 68729 |
| 8 | NEG.  FOR QUANTITATION OF POSITIVES, SEND SERUM FOR HCG. | 2604 |
| 9 | *null* | 4 |
| 10 | POSITIVE *.  FOR QUANTITATION OF POSITIVES, SEND SERUM FOR HCG. | 104 |
| 11 | EQUIVOCAL.  FOR QUANTITATION OF POSITIVES, SEND SERUM FOR HCG. | 40 |

*Figure 1: Comments and counts on pregnancy tests*

We used a SQL WINDOW function to select the first entry for every patient, based on the time they were admitted to hospital or the time the pregnancy test was taken (whichever occurred first), to eliminate duplicate patient entries. Once our pregnant group was defined, we calculated the minimum and maximum age of pregnant women (18 and 52, respectively), and used these to filter our 'not pregnant' women to create our control group.

In order to compare the top 10 diagnoses-related groups (DRGs) for pregnant and not-pregnant women, we want to disregard pregnancy-related diagnoses, as they are not applicable to not-pregnant women. The DRG-code range for pregnancy-related diagnoses is 768-833 (HCFA) and 540-566 (APR). HCFA entries don't have a severity or mortality entry associated with them. The database still uses old DRG entries for pregnancy, including 765, 766, 767.[8] By creating CTEs for each DRG type and filtering DRG codes to exclude the above code ranges (e.g., WHERE drg_type='HCFA' AND drg_code NOT BETWEEN '765' and '833'), we

[8] New DRG Codes for C-sections and Vaginal Deliveries (2019) Retrieved December 12, 2024, from https://www.mhswi.com/newsroom/New-DRG-codes-for-C-sections-and-vaginal-deliveries.html

were able to combine the resulting CTEs using the SQL UNION operator and compare the top 10 DRGs in the pregnant group with the control group.

We used WINDOW functions to calculate 30-day readmissions for both groups. We first determined the days to readmission using the DATE_DIFF function to calculate the difference in days between discharge time and the next admission time, which was evaluated using the LEAD() function to find the next admission time for each patient (e.g., LEAD(admittime) OVER (PARTITION BY subject_id ORDER BY admittime)). The results were aggregated to compare the 30-day readmissions rate for pregnant women to the control group.

## Results

### *Age distribution*

To avoid age bias, ages 18 to 52 years were selected for both the pregnant population (comparison group) and the non pregnant population (control group). Of the sample size of 43711, 31,187 *(71.34%)* are not pregnant, 12,524 *(28.65%)* were pregnant. The bar graph in **Figure 2** shows the distributions of the pregnant and non-pregnant population. As expected, the non-pregnant population is representative of the general population with a distribution across the age range 18-52 years while the pregnant population is mostly between ages 18-45 years. Unlike the non pregnant group, there are less older people above 40 years in the pregnant group making the pregnant women graph tend towards normal distribution.

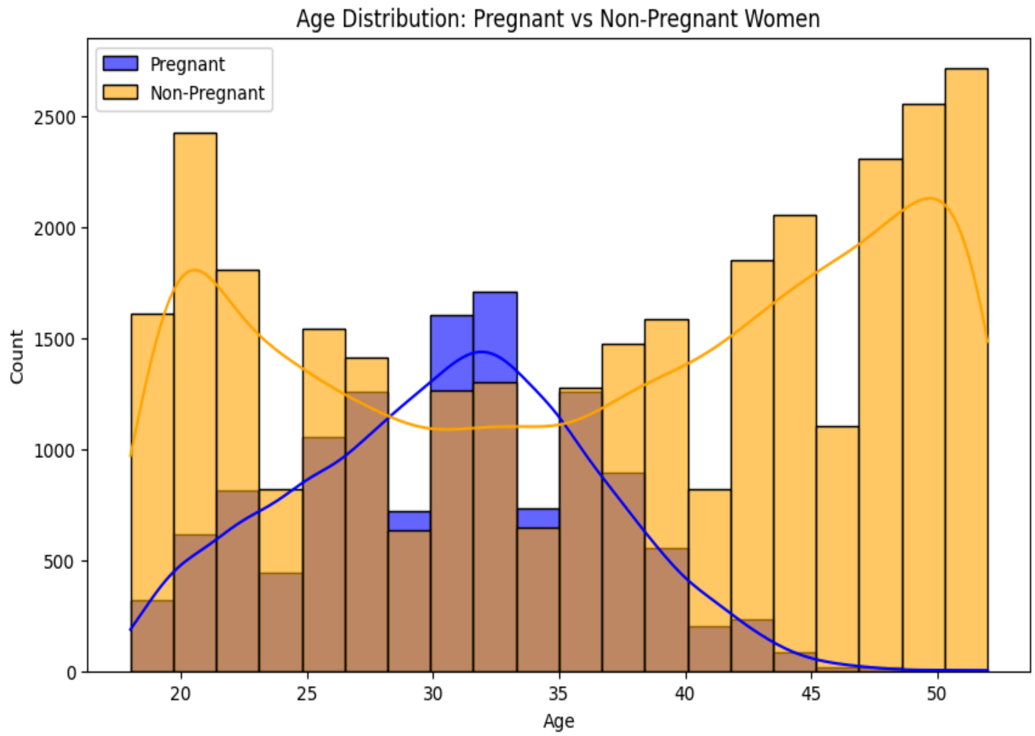


*Figure 2: Differences in age distribution between populations*

*Diagnosis-Related Groups (DRGs) for pregnant and non pregnant women*

One conclusion from the comparison of the top 10 DRGs (see **Figures 3 & 4** below) is the notable variance in scope between different DRGS. Some DRGs are very general, such as "psychoses" for many mental health conditions or "moderately extensive procedure unrelated to principal diagnoses", which is a highly generalized category that includes a variety of procedures. Other groups are narrower and more clearly defined, such as the delineation of "seizures w/o MCC" as opposed to the more general "seizures" group. A notable consequence of this variability in scope is that a "top 10 ranking" of DRGs will more likely reflect differences in definitions rather than true differences in prevalence.

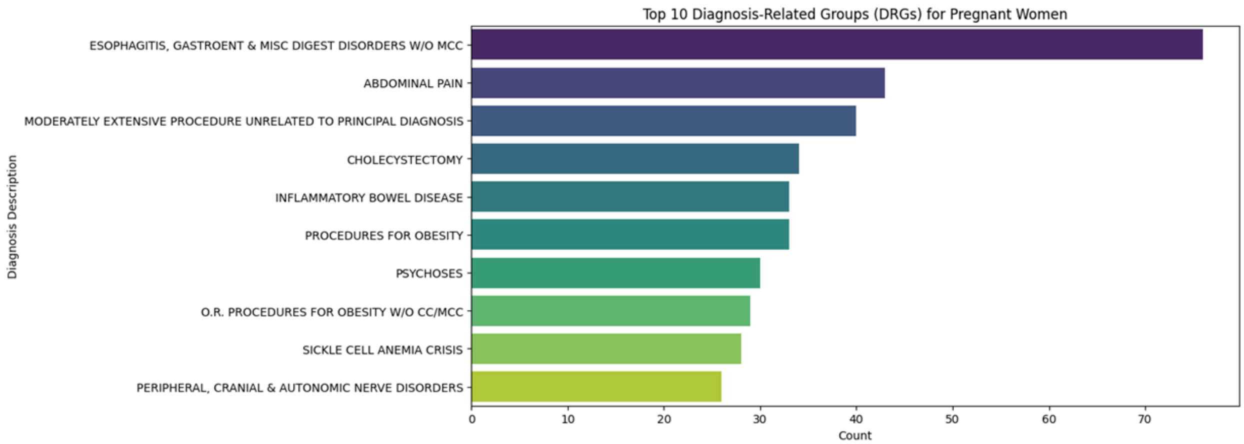


*Figure 3: Top 10 DRGS for Pregnant Women*

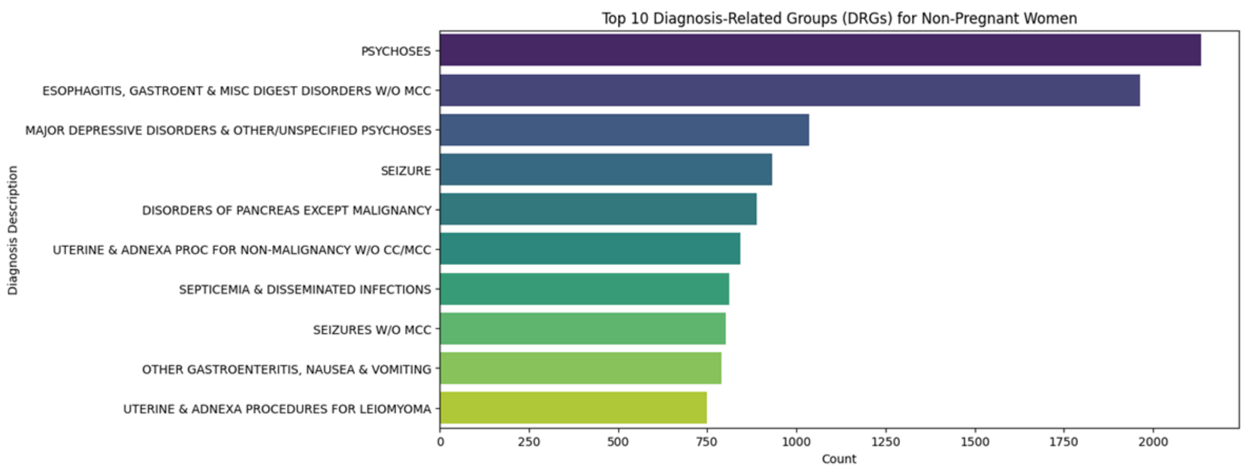


*Figure 4: Top 10 DRGS for Non-Pregnant Women*

*Intensive care unit (ICU) and readmission rate*

The readmission rate for not-pregnant individuals was 20.68%, significantly higher than the 15.75% observed among pregnant individuals, shown in **Figure 5**. The not pregnant group included 31,187 individuals, of whom 6,449 were readmitted, compared to 12,524 total individuals and 1,972 readmissions in the pregnant group. This disparity suggests notable differences in healthcare needs, conditions, or other factors influencing readmission rates between the two groups.

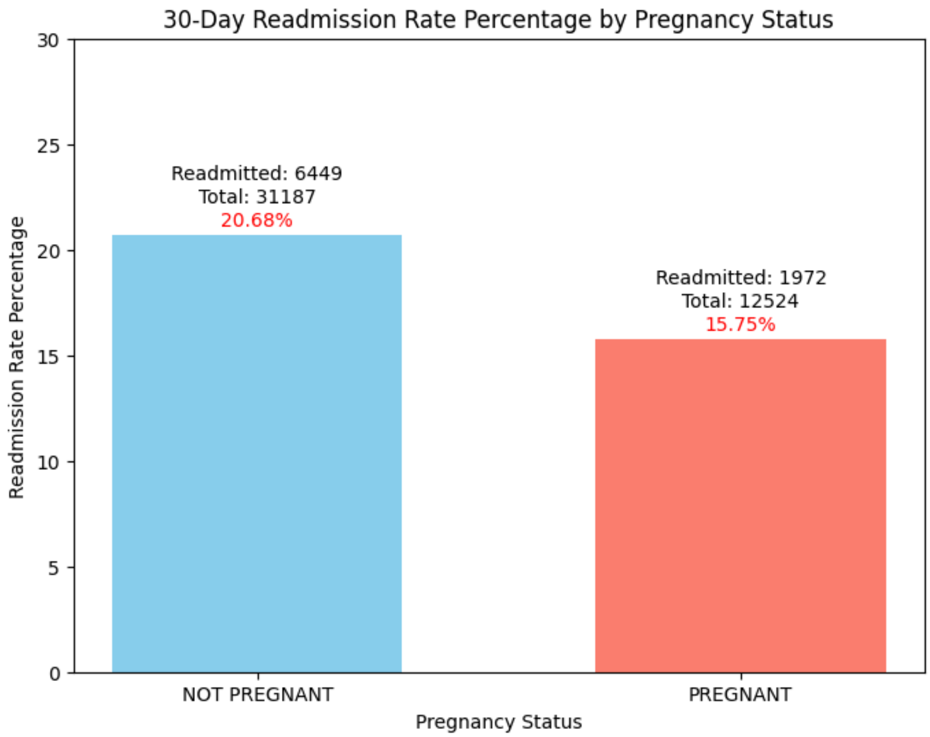


*Figure 5: 30-Day Readmission Rate by Pregnancy Status*

## Conclusions & Discussion

In our study, the non-pregnant group included a higher proportion of older individuals compared to the pregnant group. This distinction highlights the critical role of age as a risk factor and its potential confounding effect on hospital utilization and disease burden. Age is well-established in the literature as both a common risk factor and a confounder for various health outcomes[9]. As individuals age, the likelihood of developing comorbidities, requiring medical attention, and experiencing hospital readmissions tends to increase.

Our findings suggest that age contributes significantly to disease recurrence, leading to increased hospital utilization and higher readmission rates among the non-pregnant population, which comprises a greater proportion of older women. This trend is also reflected in the diagnosis-related groups, further underscoring the relationship between age, disease burden, and healthcare resource utilization.

One clear take away from the comparison of the top 10 DRGs is the notable variance in scope between different DRGS. Some DRGs are very general, such as “psychoses” for many mental health conditions or “moderately extensive procedure unrelated to principal diagnoses”, which is a highly generalized category that includes a variety of procedures. Other groups are narrower and more clearly defined, such as the delineation of “seizures w/o MCC” as opposed to the more general “seizures” group. A notable consequence of this variability in scope is that a “top 10 ranking” of DRGs will more likely reflect differences in definitions rather than true differences in prevalence.

On a similar note, standards for classification and DRG coding appear to vary between pregnant and non-pregnant women, especially for mental health diagnoses. Interestingly, while the general category “psychoses” (which includes several common diagnoses such as anxiety) was the most common DRG for non-pregnant women, this same DRG code was only the seventh most common for pregnant women. This difference should not be taken as a clear indicator of improved mental health for pregnant women; after all, antenatal mental health concerns are quite frequent[9]. However, pregnant women’s mental health concerns are typically viewed through the lens of their antenatal mental health (as opposed to their mental health more generally) and classified using a separate DRG code. Due to the splitting of pregnant women’s mental health into separate classifying “buckets” during data entry, subsequent analyses must be careful to use adequate logic to reflect multiple potential DRGs or other classifications and ontologies.

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[9] Howard, L. M., & Khalifeh, H. (2020). Perinatal mental health: a review of progress and challenges. *World Psychiatry*, *19*(3), 313-327.

Our analysis of 30-day readmission rates revealed a notable disparity between pregnant and non-pregnant individuals, with the non-pregnant group exhibiting a significantly higher rate of 20.68% compared to 15.75% for pregnant individuals. Several factors likely contribute to this difference. Pregnant individuals often receive comprehensive and routine post-discharge care, which may help mitigate the risk of readmissions. In contrast, the non-pregnant group was generally older and exhibited higher rates of chronic conditions such as mental health disorders, seizures, and septicemia, all of which are strongly associated with increased readmission risk. Additionally, the observed lower readmission rate among pregnant individuals may partially reflect potential misclassification, as our method for identifying pregnancy relied on ICD codes or HCG lab results, which may have led to some patients being incorrectly classified.

The findings suggest that the lower readmission rate in pregnant individuals likely results from a combination of enhanced care practices, differences in underlying health conditions, and potential limitations in classification accuracy. These results emphasize the need for targeted interventions to address the higher readmission risk in non-pregnant individuals, particularly those with chronic and mental health conditions. Adapting successful prenatal and postpartum care strategies for the broader female population could also help improve outcomes.

Our analysis raises several key points for consideration in healthcare policy and practice. Firstly, early identification and targeted care; pregnant women with certain conditions like sepsis or preeclampsia are at a higher risk for readmission shortly after discharge. By identifying these high-risk cases early, we can better target care programs to reduce readmissions and improve maternal outcomes. Secondly, limitations of readmission metrics; there's growing concern about using maternal postpartum readmission rates as a metric for quality care, as this could lead to disincentives in reimbursement models. Readmission patterns vary by diagnosis, and understanding these nuances is critical for accurate quality assessment and improvement. Lastly, chronic conditions and mental health; our findings also point to the importance of addressing underlying chronic conditions and mental health in both pregnant and non-pregnant women. For example, issues like psychiatric diseases, substance use, and hypertension are strong predictors of readmission, suggesting the need for tailored care strategies. Ultimately, our research suggests that adapting successful postpartum care strategies for the broader female patient population, particularly for those with chronic conditions, could improve outcomes not only for pregnant women but for all women in similar health situations. Further research should explore the role of factors such as comorbidities, socioeconomic status, and access to care in shaping these disparities, in order to inform strategies to reduce readmissions for high-risk populations.

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**Contributions:**

**Tolu:** Filtered the created CTE  based on ICD codes OR HCG  to include patients with null ICD codes. Selected unique patients based on the first positive (for pregnant women) and negative status (for non pregnant women). Selected event time based on admission OR sampling time. Researched on readmission rate and age distribution of pregnant vs non pregnant women. Presented and wrote on age distribution in the results and methods section.

**Anne:** Worked with Victoria to set up the BigQuery sharing system. Calculated readmission rate and developed the readmission query with the help of Victoria. Exported queries from BigQuery to Collab notebook to create the graphs on age distribution, DRGs, and readmission rates presented in our presentation and paper. Responsible for writing part of the results and discussion regarding 30 day readmission findings.

**Adam:** Researched MIMIC-IV table structure and wrote initial queries and joins to connect tables. Collaborated with Victoria on the ICD_Code search. Set-up final presentation outline and template, first draft of team slides, and proof-read final submissions. Presented and wrote the final results and conclusions section for the top 10 DRG comparison analysis and proofread final essay.

**Brianna:** Background literature review for initial study themes, MIMIC-IV dataset, and subsequent implications. Worked on the design, writing, and troubleshooting of the SQL queries for the initial table creation for participants of interest. Worked on descriptive and analytical visualisations of the identified participants utilising sklearn, matplotlib, and pandas in python. Involved in the refinement of the queries for the calculation of the readmission rates. Further research on wider implications and future research directions.

**Victoria:** Researched pregnancy-related ICD-9/10 codes. Investigated and analyzed ‘labitems’ and ‘labevents’ tables in MIMIC-IV using SQL to develop effective SQL queries and CTEs that determine the result of HCG lab tests. Integrated these CTEs into the relevant SQL query to categorize patients as pregnant or not pregnant. Researching pregnancy-related DRGs by DRG type and creating two corresponding CTEs to exclude data entries with those pregnancy-related DRG codes. Combining the resulting CTEs to get the top 10 non-pregnancy related DRGs for pregnant women. Edited the readmission query Anne worked on to calculate the days to readmission based on the difference between discharge time and next time of admission instead of admit time and next time of admission (based on Brianna’s input). Responsible for presenting and writing Methods section.