The Development of CCNC's ED Risk Score

Community Care OF NORTH CAROLINA

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KEY POINTS FROM THIS BRIEF:

- Community Care of North Carolina (CCNC) has studied emergency department (ED) utilization patterns in the Medicaid population for over two decades, gaining insights into how to identify impactable utilization trends.
- Our experience has shown that traditional algorithms that focus measurement and intervention on a select set of "avoidable" diagnoses is a potentially myopic approach for impacting ED utilization through care management.
- While many ED users are "once and done" patients who do not return during the performance year, a distinct subgroup of ED patients have a higher probability of repeat ED visits. These patients often present with complex clinical conditions, behavioral health needs, and social vulnerabilities that are more appropriate for care management resources.
- Using machine learning, CCNC developed a predictive model to stratify patients based on their propensity to return to the ED after an initial visit. This model informed the creation of the ED Risk Score, a scalable tool for identifying individuals at high risk of returning to the ED. This tool can then be applied to population data to assist in evaluating the effectiveness of care management and other interventions.

Background

Emergency departments (ED) serve an important role in the healthcare ecosystem, yet they can easily be over-utilized resulting in higher costs and poorer care coordination.[1,2] How one measures ED utilization can drive how interventions are implemented and how success from those interventions is determined. Because there are often valid and appropriate reasons to use the ED, the focus of measurement tends to be on identifying specific visits that could have otherwise been avoided through some intervention.

A common temptation is to focus on the diagnoses associated with individual visits to determine whether the visit was likely "avoidable" or unnecessary. Several out-of-the-box algorithms exist for this purpose, employing concepts such as "avoidable," "preventable," or "non-emergent." CCNC has experience implementing many of these, including 3M's potentially preventable ED visits,[3] NYU's ED algorithms,[4] and locally developed lists of non-emergent diagnoses created by a state-convened clinical body. Our experience has shown that these traditional algorithms tend to be overly conservative in what is deemed "avoidable". Understandably, if your intent is to measure what is "avoidable", you would lean towards focusing on those diagnoses that have a high certainty of being "avoidable". However, the reality is that the determination of what is avoidable is not as certain as these algorithms would lead you to believe. There seems to be tremendous ambiguity and disagreement about what could be avoidable by just looking at primary diagnoses. To the credit of the NYU algorithm, they acknowledge this level of uncertainty and provide probabilities associated with individual diagnoses. However, when implementing a measure, one must set a threshold for where the line is drawn for how "avoidable" is defined. Aside from these limitations, the NYU algorithm – possibly the most commonly used algorithm in measuring avoidable ED utilization – was originally developed during the 1990's; while there have been some modest updates, including mapping to ICD-10, it's still fundamentally based upon clinical judgments that are roughly 30 years old4.

Keeping these limitations in mind, focusing solely on visits deemed "avoidable" may present an incomplete picture of ED utilization and overlook valuable opportunities to improve patient outcomes. While such approaches may aim to be conservative in estimating otherwise unnecessary visits, they inadvertently exclude a wide range of ED encounters that are demonstrably avoidable. This narrow focus can result in underestimating the true burden of repeat ED use and the complexity of the patients who drive it. Additionally, while many ED users are "once and done," a smaller, high-risk subgroup frequently reappears, often burdened by chronic conditions, behavioral health issues, and social vulnerabilities. These repeat visits not only strain emergency services but also contribute significantly to rising healthcare costs, making targeted interventions both a clinical and financial imperative. There is likely a significant opportunity to impact utilization among these patients, an opportunity that would often be missed if focused on a narrow set of theoretically "avoidable" diagnoses.

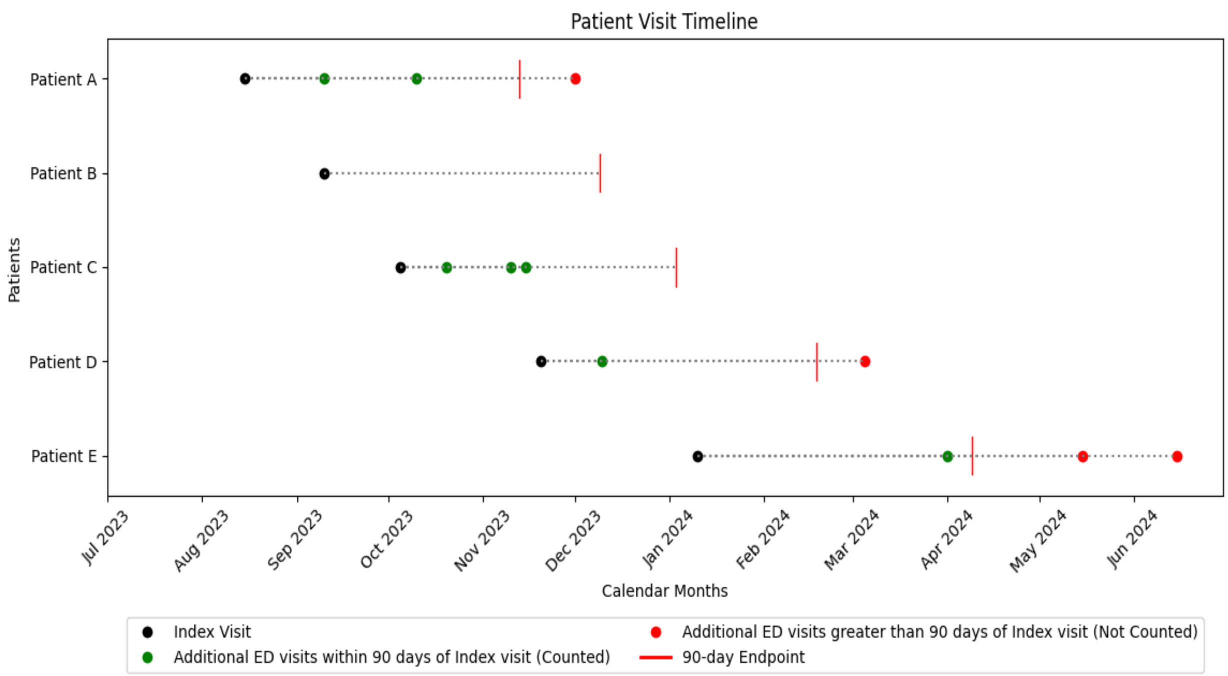
Community Care of North Carolina (CCNC) has spent over two decades analyzing ED patterns within the Medicaid population. Of note, while there are potentially many strategies to impact utilization, our focus here is on care management interventions and what is impactable with regards to care management. Taking these learnings, we sought to create a novel way to capture more comprehensive opportunities to impact ED utilization; in the following sections of this data brief, we share some of those insights. Our work led to the development of a machine learning-based predictive model referred to as the ED Risk Score. This scalable tool is designed to identify individuals at greatest risk of repeat ED visits. The purpose of this data brief is to share our learnings around ED utilization patterns among the Medicaid population and describe the process of developing the ED Risk Score. Its application will be described and evaluated in a later data brief.

ED Return Rate

The first thing we needed to do was develop an outcome metric by which to build the predictive model. Upon analyzing our Medicaid population during the most recent one-year period, roughly three-quarters of the members had never used the emergency room and less than 15% visited the ED once during the year. Between 5% and 10% of the entire Medicaid population used the ED more than once during a given year. Said another way, only about 1/3 of the patients who ever go to the ED returned during the year. Being able to identify and focus on this one-third of ED users is necessary to effectively prevent further ED visits in this population. Since the primary goal of a care management intervention is to prevent further visits to the ED, we developed a metric – the ED Return Rate – that would hone in on that particular outcome.

In creating the ED Return Rate, we pulled all ED visits that occurred during a one-year period (July 2023 – June 2024) for members enrolled in one of two Medicaid prepaid health plans and identified the first visit during the year as the index visit. We then looked at the period after their index visit to determine whether the patient returned to the ED in the following months (see appendix for more information about the study population). To better enumerate repeat ED utilization, we developed an outcome variable called the ED Return Rate, defined as the number of additional ED visits incurred within 90 days following an index visit, expressed as an annualized rate per 1,000 members. This rate-based approach was chosen over a binary outcome to capture the intensity of ED recidivism, recognizing that one return visit often leads to multiple subsequent visits. We chose the 90-day follow-up period to be able to detect the most proximal impact from any intervention. Figure 1 provides an example of 5 mock patients to illustrate how the calculation is made.

Figure 1: The Patient Visit Timeline Diagram: How ED Return Rates are Calculated



Based on the patient visit timeline diagram, each patient's additional ED visits after the index visit are evaluated to determine how many are counted toward the ED Return Rate, which includes only those occurring within 90 days of the index visit. Patient A had 2 additional ED visits within 90 days, which are counted, and 1 visit beyond 90 days, which is not counted. Patient B had no additional ED visits beyond the index visit, so no follow-up ED visits are counted. Patient C had 3 additional ED visits, all within the 90-day window, and all are counted. Patient D had 1 additional ED visit within 90 days, which is counted, and 1 visit beyond 90 days, which is not counted. Patient E had 3 additional ED visits, of which 1 occurred within the 90-day window and is counted, while the remaining 2 occurred after 90 days and are not counted.

Predictors of ED Return Rate

Using this outcome, we evaluated several potential predictors of ED return, including prior ED utilization, clinical complexity (as measured by the Johns Hopkins ACG® System[5]), behavioral health indicators, social vulnerability and emergent/non-emergent indicators associated with the index visits. We felt it would be instructive to show how each individual variable correlate with this new outcome metric. For illustrative purposes, we present the bivariate relationship between the ED Return Rate and each variable used in the predictive model for the ED Risk Score. Each bar shows the ED Return Rate for patients within those subgroups. The error bars show the 95% confidence interval for each of the calculated rates. Note that these calculations reflect the ED Return Rate following an index ED visit, and not the baseline utilization rate among all members of that subgroup. For context, the baseline average annualized utilization rate among our Medicaid population is approximately 500 ED visits per 1,000 members. Hence an ED Return Rate near 500 would suggest that the person's subsequent utilization is no different than what is typically expected for the population at any point during the year, meaning that going to the ED once did not meaningfully change the trajectory at which that patient or group of patients accesses the ED going forward. However, rates that are significantly higher than 500 indicate a significantly higher propensity for returning to the ED again.

Starting with the variables most associated with a higher ED Return Rate, we see that the more complex a patient becomes, the greater the likelihood they will return to the ED following their index visit. We used the Johns Hopkins ACG® System[5] to identify the complexity of each patient in this evaluation. The ACG System goes beyond identifying discrete chronic conditions by considering the overall clinical burden including complex comorbidities and the patient's comprehensive healthcare needs. By entering complete claims information into the system, including diagnoses, medications and procedures, the ACG System assigns each patient to one of approximately 210 Adjusted Clinical Groups (ACGs). ACG categories are health status categories defined by morbidity, age, and sex in addition to clinical morbidities.[5]

Figure 2: ED Return Rate by Adjusted Clinical Group (ACG) Code

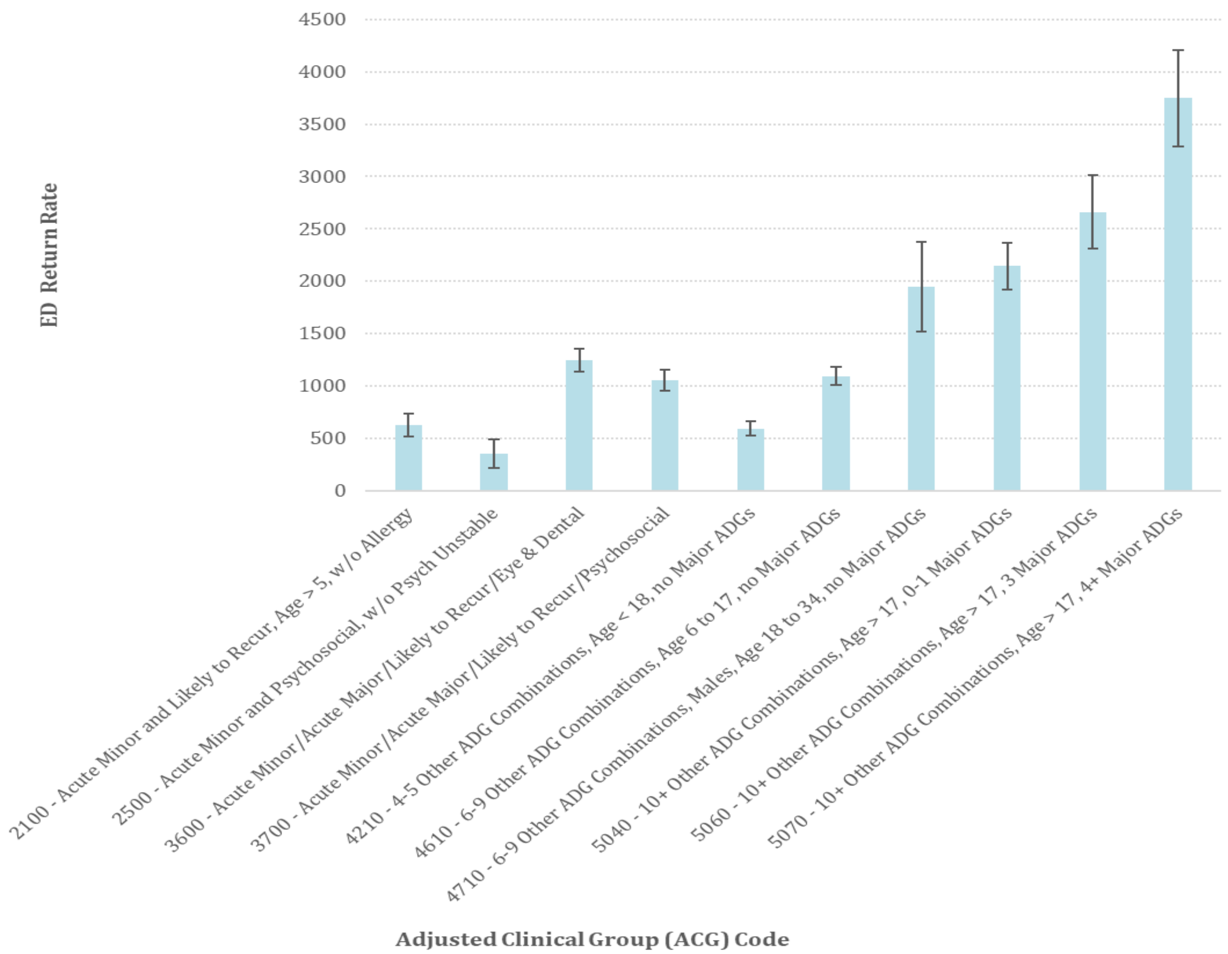
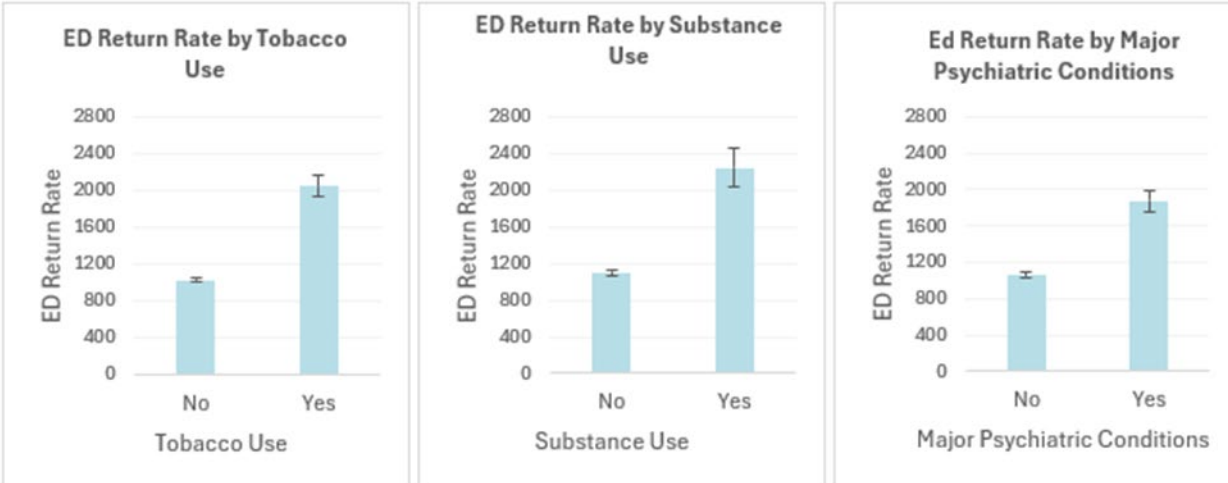


Figure 2 above shows the ED Return Rate for a select set of ACG codes. We are unable to display all 210 ACGs but have chosen several representative categories to illustrate the wide variation across different ACG groups in terms of this new outcome measure – ED Return Rate. The figure suggests that patients in the ACG groups defined as 2100, 2500 and 4210, for example, have a very low likelihood of returning to the ED following an initial visit, and therefore care management would likely have limited impact on reducing future utilization. However, patients in the 5070 ACG code have an ED Return Rate that is almost 8x higher than normal.

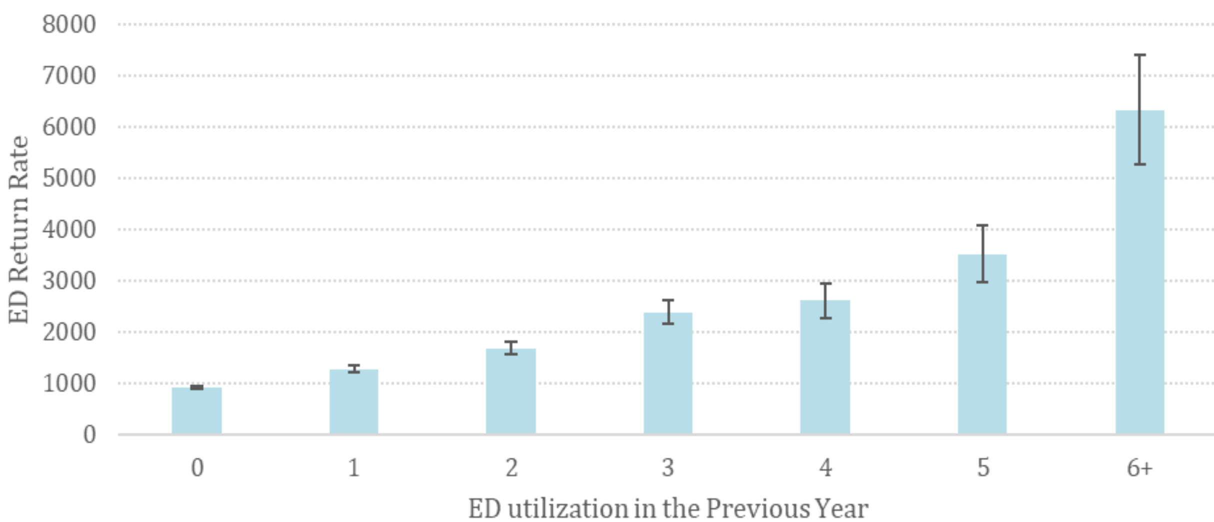
For illustrative purposes, we also display the relationship between ED Return Rate and three clinical indicators derived from the Johns Hopkins ACG® System[2] – substance use, tobacco use and the presence of a major psychiatric condition (Figure 3). While each of them shows a strong correlation with the ED Return Rate, each is at least partially accounted for by the ACG Code described above.

Figure 3: ED Return Rate by substance use, tobacco use, and major psychiatric condition



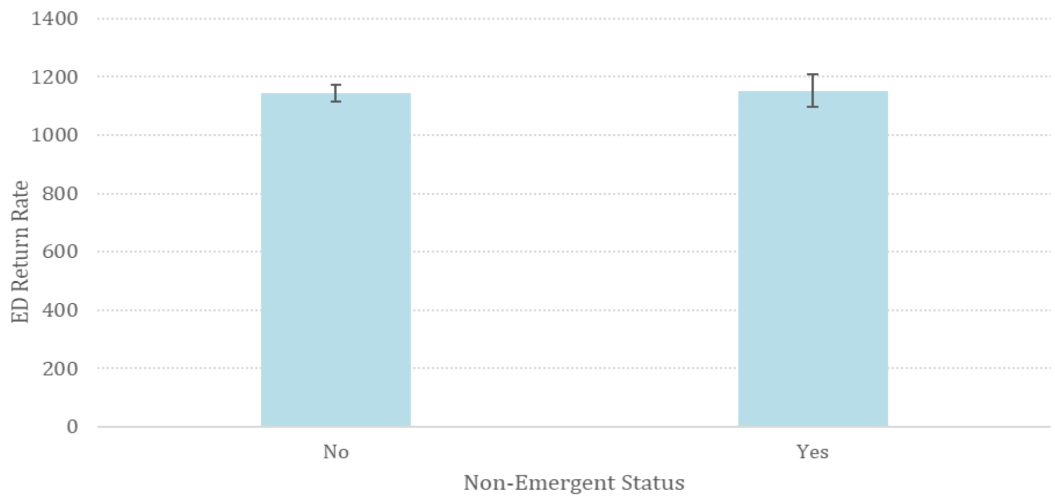
Another significant predictor of ED Return Rate is the person's ED utilization during the year prior to the index visit. As illustrated by Figure 4 below, the more times a person has used the ED in the past, the more likely they are to return to the ED in the future. Not surprisingly, patients who are accustomed to accessing ED for their healthcare needs are more likely to continue doing so in the future. This pattern of behavior presents a potentially ripe opportunity for impacting future ED utilization.

Figure 4: ED Return Rate by Historical ED Utilization



On the other hand, whether the index visit was considered “avoidable” made virtually no difference in their ED Return Rate. For this analysis, we applied the NYU Algorithm for emergent and non-emergent ED visits. A total of 18.8 % of the patients in this study had an index visit that was deemed ‘non-emergent’ per the NYU Algorithm. The small percentage reflects the fact that relatively few visits meet the strict definition of what is a ‘non-emergent’ visit as defined by many of the traditional algorithms for such purposes. This lack of an association may partially be due to the limitations of any algorithm to accurately distinguish between emergent and non-emergent visits. That said, if you at least assume that the patients in the Non-emergent group (“Yes” bar in the figure 5) represented those with a greater likelihood of being truly avoidable, you might expect to at least see a trend in the right direction (i.e., the Non-emergent group having a higher ED Return Rate). However, the lack of any trend in that direction casts doubt on there being any meaningful relationship between true “avoidable”-ness of a single ED visit and the likelihood of returning to the ED.

Figure 5: ED Return Rate by Non-Emergent Status



In terms of demographics, we studied the relationship between ED Return Rate and Sex, Race and Ethnicity. We found female patients were only slightly, and non-significantly more likely to return to the ED compared to males. Of note, pregnant women are part of a distinct set of ACG codes, so any differences driven by pregnancy are captured by virtue of those specific ACGs.

Figure 6: ED Return Rate by Sex

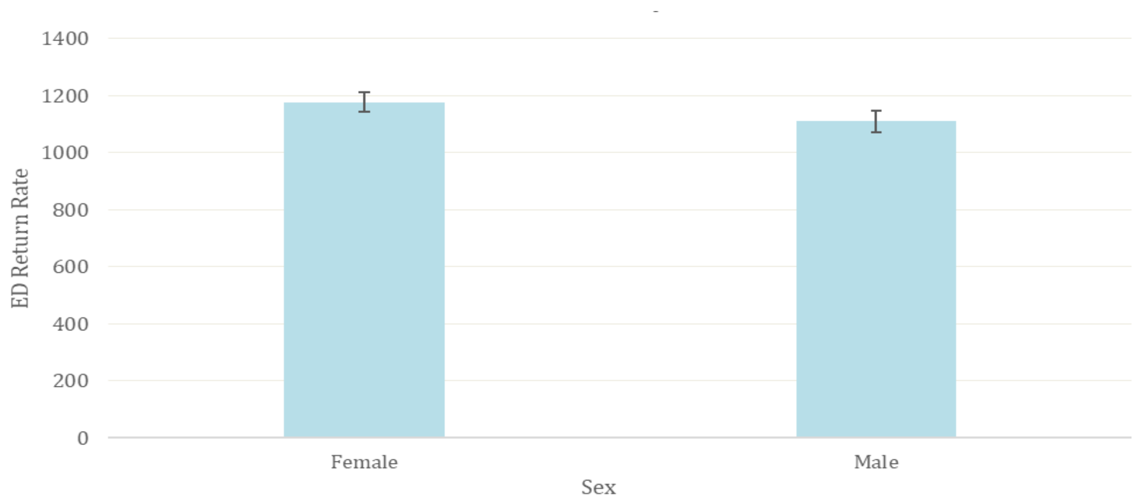
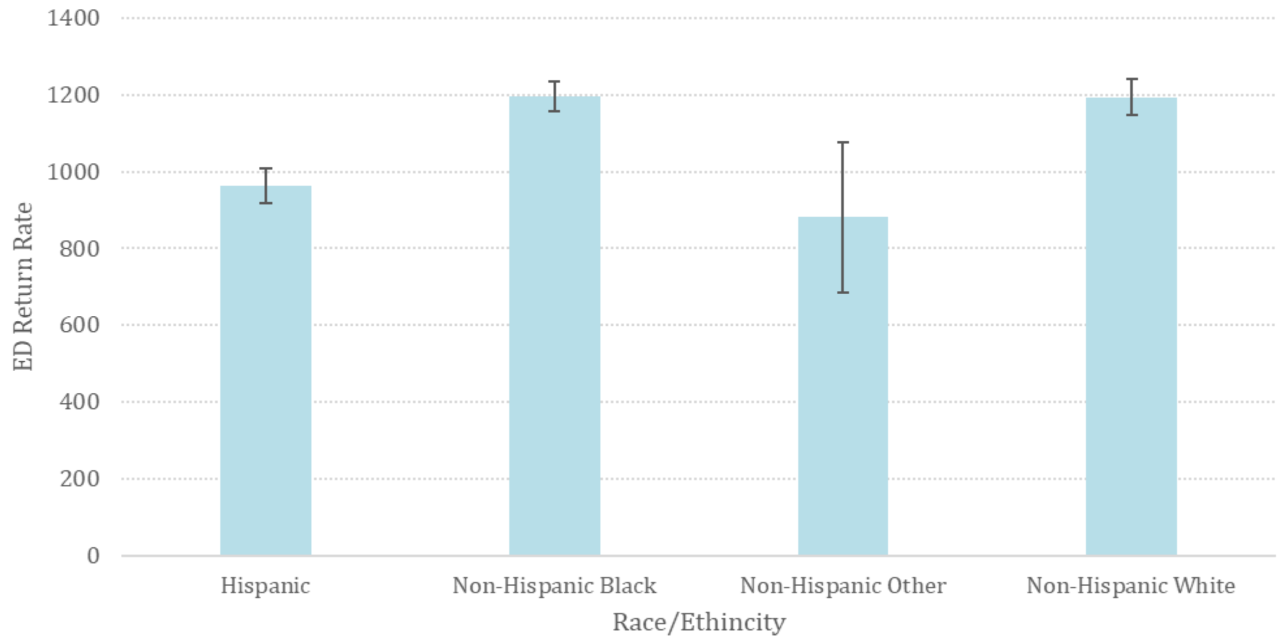
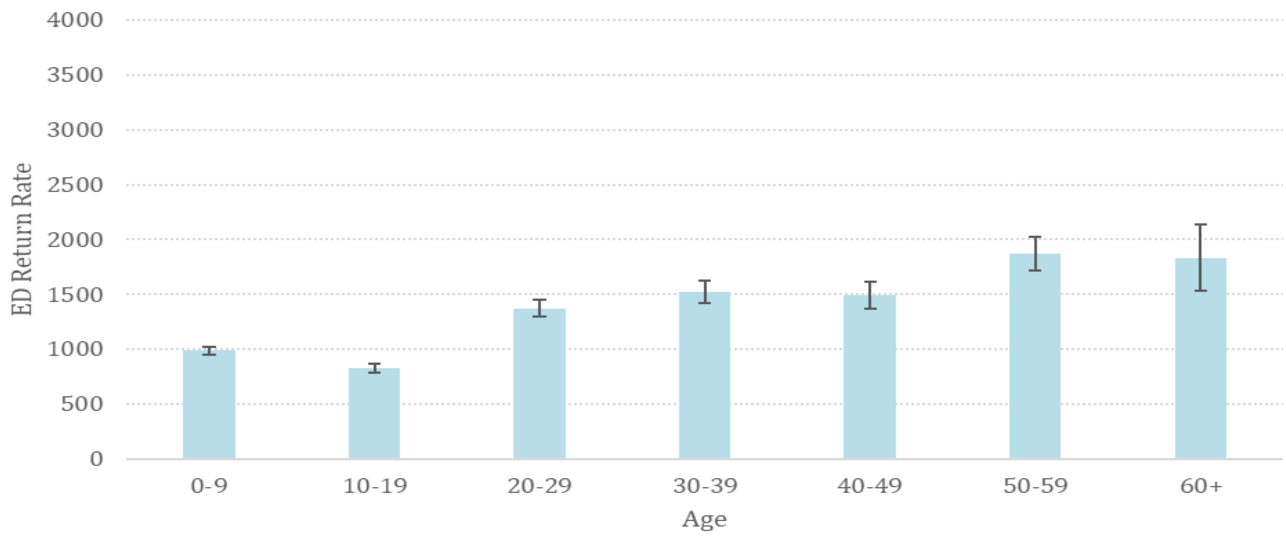


Figure 7: ED Return Rate by Race and Ethnicity



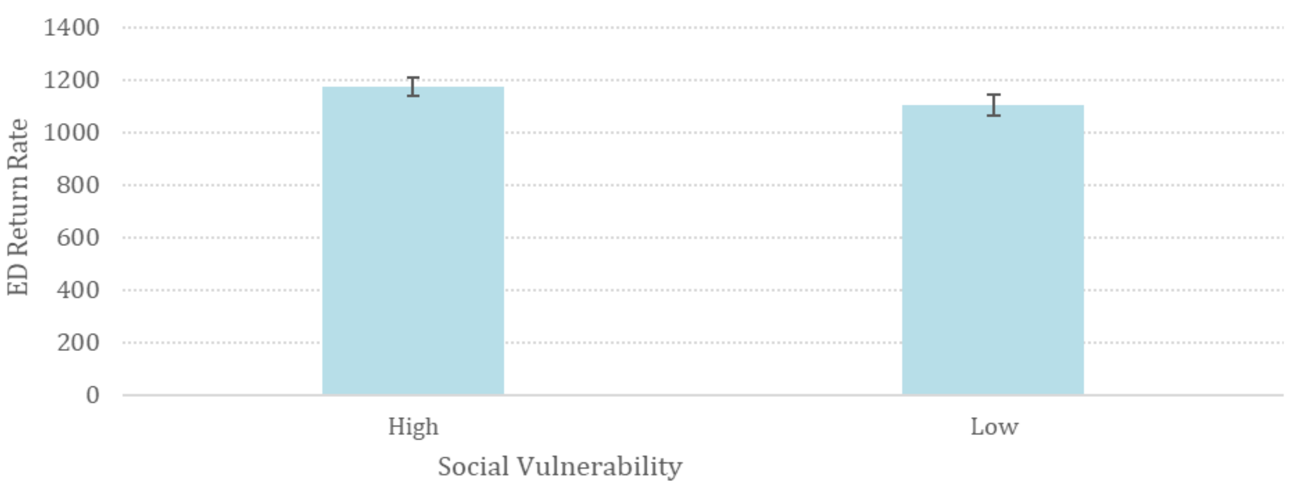
The ED Return Rate is higher among older patients. This is somewhat to be expected given that older patients tend to have greater clinical complexity which we've already established is associated with a higher ED Return Rate.

Figure 8: ED Return Rate by Age



Another potential predictor of ED Return Rate is the social vulnerability. Patients may be more likely to return to the ED if they have limited access to basic necessities such as housing, transportation and food. While social determinants at the individual level likely have some contribution to ED utilization, there is a temptation to use aggregate measures of social vulnerability, such as the Social Vulnerability Index[6] associated with members within a specific zip code to enhance the predictability of future ED utilization. However, when we applied this concept to our data, the figure below clearly illustrates that this approach does not yield any benefit for separating those who return to the ED from those who do not.

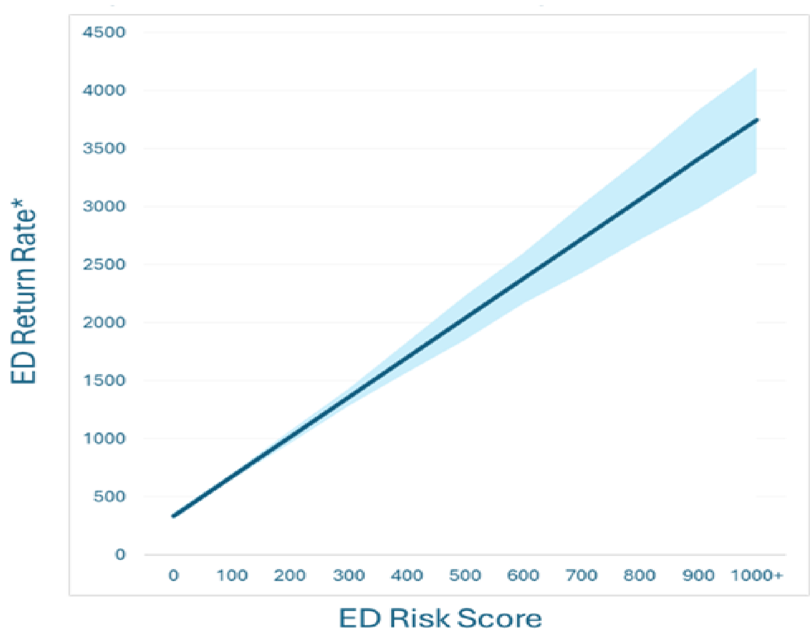
Figure 9: ED Return Rate by Social Vulnerability Status



ED Risk Score

Given the inherently complex interplay of the various factors that drive the ED Return Rate as demonstrated above, we created a new variable – ED Risk Score – to stratify patients based on their overall risk or likelihood of returning to the ED following their index ED visit. The data, both the individual predictors and the ED Return Rate outcomes, were used in a series of predictive analytics to maximize the predictability of the ED Return Rate following an index ED visit. The details of the score are proprietary but are comprised of the elements described in the above section. By combining the collective drivers of ED recidivism, we were able to arrive at a more accurate and holistic predictor of the risk associated with any one patient. Applying the principles of machine learning allows us to fine tune the model over time as more data and experience accumulates. To maintain consistency with our existing Impactability scores we mapped the risk scores to a scale from 0-1,000, with 1,000 reflecting the highest risk patients. The figure below shows the resulting trendline between the ED Risk Score and the ED Return Rate, with the line showing the predicted return rate from the predictive model, and the bands illustrating the 95% confidence intervals along the trajectory.

Figure 10: Expected ED Return Rate by ED Risk Score



*ED Return Rate = number of ED visits incurred in the 90 days following an index visit annualized per 1,000 members.

The ED Risk Score, scaled from 0 to 1,000, enables stratification of patients based on their likelihood of returning to the Emergency Department (ED), offering a data-driven framework for understanding utilization patterns. We applied the score to the original population to see what differences emerged in terms of individual characteristics. Table 1 displays the characteristics associated with patients who fall into each one of three broad risk stratification buckets (Low (0-199), Medium (200-499), High (500+)). Patients with higher scores were more likely to be older and female with greater medical and behavioral health complexities, along with a history of using the ED in the recent past.

Table 1: ED Return Rate by Social Vulnerability Status

Characteristic	Low	Medium	High
Total N	25,240	16,274	5,426
Mean Age	15.2	22.0	30.4
% Underage 21	76.6	56.6	32.4
% Female	48.1	59.3	67.3
% Hispanic	24.2	20.2	13.6
% White	43.9	46.8	46.5
% Black	45.7	43.2	45.2
% Tobacco Use	6.2	16.0	31.3
% Substance Use	1.5	5.1	13.5
% Major Psychiatric Condition	4.5	14.5	29.2
% High Social Vulnerability	56.6	56.9	58.7
% Multi-Morbidity High/Medium Complexity	15.8	35.4	54.7
% with any ED Utilization (Pre-Period)	10.1	37.9	88.8

Conclusion

Community Care of North Carolina (CCNC) has spent over two decades studying emergency department (ED) utilization among Medicaid patients, gaining deep insights into how to measure, understand, and impact ED use. While most ED users are "once and done" patients, a distinct subgroup demonstrates a high likelihood of repeat visits, often driven by complex clinical conditions, behavioral health needs, and social vulnerabilities. Applying algorithms that focus on a narrow set of "avoidable" diagnoses or using geographic location to make assumptions about individual social determinants has limited value-add when it comes to predicting future ED utilization. Recognizing the limitations of existing tools to assess patient-level risk, CCNC developed a predictive model using machine learning to stratify patients based on their propensity to return to the ED after an initial visit. This model informed the creation of the ED Risk Score—a scalable, data-driven tool designed to identify high-risk individuals. The score integrates demographics, prior ED utilization, clinical complexity, and social vulnerability to provide a comprehensive measure of future ED risk. The ED Risk Score offers a robust framework for targeting interventions, optimizing resource allocation, and ultimately reducing unnecessary ED utilization across the Medicaid population. Future data briefs will describe its application in risk stratification and evaluating the effectiveness of care management.

Appendix

Methodology

The study sample included a cohort of 46,940 unique patients who were enrolled in Medicaid managed care prepaid health plans and had at least one ED visit between July 1, 2023, and June 30, 2024. For each patient, the first ED visit during this period was designated as the index visit, serving as the anchor point for evaluating subsequent ED use.

To contextualize the study population and inform the modeling strategy, we conducted a preliminary analysis of ED utilization across the broader Medicaid managed care population. This analysis revealed that 78.3% of members did not visit the ED at all during the year, 13.3% had a single visit, and only 8.4% had more than one visit. Among those who accessed the ED at least once, approximately one-third returned within the same year. This finding reinforced the importance of identifying patients at risk for repeat ED use and guided the development of our outcome variable.

To quantify repeat ED utilization, the study introduced a new outcome variable called the ED Return Rate. This metric captures the number of additional ED visits that occurred within 90 days following the index visit and expresses it as an annualized rate per 1,000 members. This rate-based approach was chosen over a binary measure (e.g., returned vs. not returned) to better reflect the intensity of ED recidivism, recognizing that a single return visit often leads to multiple subsequent visits.

The predictive model developed in this study incorporated a wide range of independent variables. Clinical complexity was assessed using the Johns Hopkins ACG® System, which assigns patients to one of approximately 210 mutually exclusive risk categories based on diagnoses, medications, procedures, age, and sex. Behavioral health indicators like substance use, tobacco use, and the presence of major psychiatric conditions were also included. Prior ED utilization, specifically the number of ED visits in the 12 months preceding the index visit, was another key predictor, as patients with frequent past ED use were found to be more likely to return.

Social vulnerability was evaluated using the CDC/ATSDR Social Vulnerability Index (SVI), which was mapped to patient ZIP codes to assess the estimated social vulnerability of the patients, and demographic variables such as age, sex, race and ethnicity were also considered. Additionally, each index visit was classified as emergent or non-emergent using the NYU ED Algorithm.

Methodology

The primary data sources were paid claims and beneficiary files from the respective Prepaid Health Plans. Data were derived from Emergency Department (ED) visit records, incorporating diagnostic codes, prior ED utilization, and demographic details such as age, sex, and payer type. The Johns Hopkins ACG® System was employed to assess patient complexity using Patient Need Groups (PNGs), which reflect overall clinical burden including comorbidities, medications, and procedures. The two highest risk PNG's within our sample were Multimorbidity High Complexity and Multimorbidity Medium Complexity. Additional clinical characteristics included indicators for major psychiatric conditions, tobacco use, and substance use. Measures of geographic-based social vulnerability were sourced from the CDC/ATSDR Social Vulnerability Index (SVI) 2022 database. ED utilization patterns were evaluated based on the frequency of prior visits, classification of index visits as emergent or non-emergent, and subsequent ED visits within 90 days post-index. The dataset comprised 46,940 unique patients who visited the ED at least once between July 1, 2023, and June 30, 2024. These variables were used to inform the development and validation of the CCNC ED Risk Score, which aims to identify individuals at elevated risk for future ED utilization.

Suggested Citation

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