Modelling the flow of patients with substance misuse through the emergency department

Final Submission

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Abstract

Emergency departments (EDs) are an indispensable health care service for Canadians from all walks of life. Central to the effectiveness of EDs is their ability to deliver timely care in urgent situations. Patients presenting with substance misuse concerns to Canadian EDs are no exception, and also require timely care. In order to identify potential barriers to rapid delivery of care for this patient subset, we investigated their ED flow characteristics using a multi-state modelling approach. All patient presentations for substance misuse in Alberta for the 2019 fiscal year were extracted from a population-based provincial dataset. After data cleaning, 2,302,147 presentations were available for analysis. Of these, 74,455 were a part of the substance misuse patient population: 49% presented with alcohol-related concerns, 12% with methamphetamine-related concerns, 14% with opioid-related concerns, and 25% with some other substance. A model with seven mutually exclusive states was developed to represent the ways in which patients can move through the ED. Patients begin in the "start" state, and then move to the "physician initial assessment" (PIA) state once they are seen by a physician. From the "PIA" state, individuals may move to the "discharge disposition" state, or the physician made decide to admit or transfer the patient instead, in which case the individual then moves to the "admit/transfer disposition decision" state. Patients may also choose to leave against medical advice ("LAMA" state). Once the admit/transfer decision is made, patients must wait before actually being admitted ("admitted" state) or transferred ("transferred" state). Subsequently, characteristics that influenced how quickly patients moved from state to state were examined. Key variables that were associated with transitions among states included patient municipality type, triage score, crowding level and diagnostic code. Both triage score and ED crowding (time to PIA $>$ 1 hr) had the strongest effect on the "start" to "PIA" transition. Patients triaged with a score of 1 (most urgent) saw the physician much faster (adjusted hazard ratio [HR]: 3.76; 95% confidence interval [CI]: 3.59, 3.94), while patients presenting to a crowded ED saw the physician much slower (HR: 0.35, 95% CI: 0.34, 0.36). Diagnostic code and patient municipality were the most influential on the "disposition decision" to "admitted" transition. Compared to patients presenting with an alcohol diagnosis, those presenting with methamphetamine-related concerns waited much longer from disposition to admission (HR: 0.56; 95% CI: 0.52, 0.59). Additionally, patients from rural remote municipalities were admitted much faster than those from metropolitan municipalities (HR: 3.06; 95% CI: 2.72, 3.45). These findings present a more nuanced analysis of the factors that influence the flow of substance misuse patients through the ED.

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1 Introduction

The emergency department (ED) is an essential element of the Canadian health care system. In the 2018-19 fiscal year, EDs in Alberta had over two million visits (Alberta Health Services, 2021). When a patient presents to the ED, a standard process is followed. First, they are registered by a triage nurse who evaluates the severity of their condition, which determines the speed at which they see a physician. Then, the patient must wait in the waiting area until they are placed in a room. After this, they are seen by a physician. The physician assesses the patient, may order tests or therapies, and makes a disposition decision on whether or not the patient can be discharged or needs to be admitted to the hospital. Once the decision is made, a discharged patient leaves the ED and an admitted patient may wait in the ED until a bed is available in the hospital. In some instances, patients may leave the ED without being discharged or admitted. Firstly, patients may leave without being seen by a physician (LWBS); this is more common for patients experiencing longer wait times (Shaikh et al., 2012; Kennedy et al., 2008). Secondly, patients may leave after being seen, but against medical advice (LAMA). Lastly, the patient may die while in the ED. It is the transitions between each of these states that is referred to as "patient flow." An example of the times and states involved is provided in Figure 1.

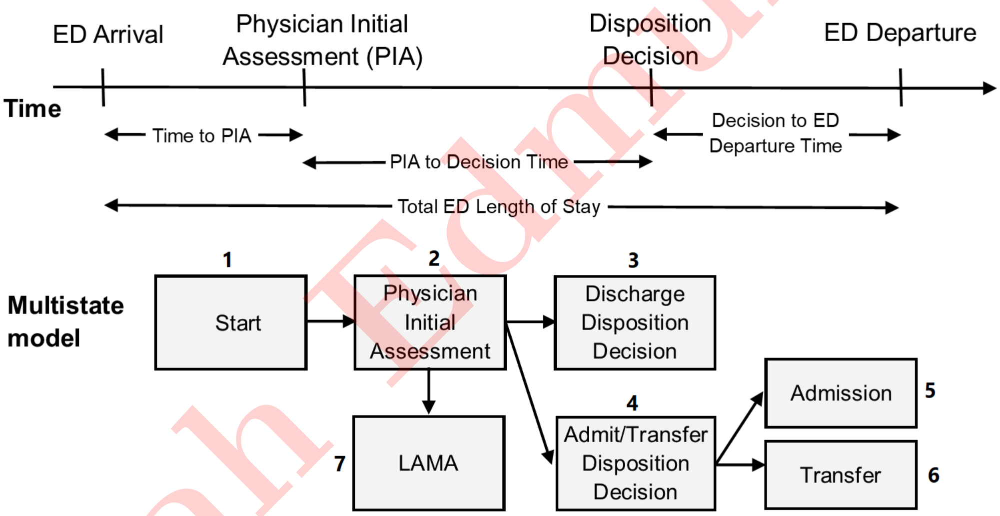

Figure 1: A multi-state diagram illustrating patient flow throught the ED.

Various factors may influence how any one individual patient flows through the ED. The geographic area of the ED is a good example; it has been shown that rural EDs have shorter overall lengths of stay than their urban counterparts (Hutten-Czapski, 2010). Homelessness is another factor that may have a significant influence. There are several reasons why homeless individuals may experience longer length of stays in the ED compared to individuals who are not homeless (Pearson et al., 2007; Schaffer et al., 2020). Firstly, staff may be reluctant to discharge patients without a fixed address, especially at night, during poor weather (i.e., winter), or if a social worker is not present (Jenkinson et al., 2020; Doran et al., 2013). Additionally, homeless patients may be disproportionately represented among frequent ED users (Mandelberg et al., 2000). This subset of frequent-use patients may experience different transition times if staff are previously aware of that individual's situation, and staff therefore expedite (or do not expedite) their treatment to the same extent as they would with an unknown, infrequent user (Malone, 1996). Chaou et al. (2016) have described other factors that increase ED wait times, such as older age, male gender, higher acuity (lower severity), and day shift arrival.

In addition to the factors mentioned above, general ED crowding also influences the flow of patients through the ED. ED crowding is commonly defined as a time from registration to physician initial assessment that is greater than one hour (Affleck et al., 2013). Crowded EDs cause increased wait times, reduced time spent with a physician, and an increased number of patients that leave without being seen (Shaikh et al., 2012). In the attempt to address ED crowding, the majority of the literature relies on administrative solutions. Firstly, increased attention to patient history during physician assessment can reduce the time to discharge by eliminating the need for unnecessary diagnostic tests (Kumar, 2012). Secondly, allocating additional resources to expedite triage can enable the quick release of community resources, especially when all beds are occupied (Human Services and Justice Coordinating Committee, 2013; Schwartz, 2015; Affleck et al., 2013). In particular, for patients who may arrive at the ED in the care of a community service worker (e.g. ambulance, police officer), rapid triage allows these care providers to return to the field more quickly (Kumar, 2012). Thirdly, certain hospitals have shown the efficacy of designating a small subset of ED resources to deal exclusively with patients presenting with certain health issues, for example, presenting with mental health and substance misuse concerns. After implementation of this strategy at Toronto's Western Hospital & St. Joseph's Health Centre, these EDs exhibited reduced wait times and decreased use of security personnel (Kumar, 2012). Another proven strategy is the "pull until full" method, which involves skipping triage when ED beds are available in order to free up triage staff (Emergency Nurses Association, 2017). Lastly, setting aside a physical space to house patients who do not require a bed or are awaiting diagnostic tests has been shown to increase ED throughput (i.e., vertical treatment space). All of the aforementioned strategies are desirable insofar as they safely decrease acute care use, as this allows for reduced ED crowding, for higher acuity patients to be seen faster, and for reduced health care costs.

Given that most large EDs in Canada experience crowding and patients experience long wait times, it is important to focus on reducing ED use for conditions that are preventable and when other health care options are available. Patients with acute substance misuse issues are a patient population where many ED presentations could be prevented. The Diagnostic and Statistical Manual of Mental Disorders defines substance misuse as "All drugs that are taken in excess" so that "normal activities may be neglected" (American Psychiatric Publishing, 2013). In Alberta between 2012 and 2017, patients with substance misuse accounted for 1% of all ED presentations (McLane et al., 2021). This percentage may seem small, but because of the large volume of ED presentations in any given year, 1% represents around 141,977 presentations in Alberta alone. Based on this large volume of presentations, it is essential that attention is given to this subset of patients.

Investigating the flow of patients with substance misuse through the ED is important as it can inform ED staff and administrators about how to reduce further injury and death in these patients. It is obvious that swift delivery of stabilizing care medications (naloxone, glucose, thiamine, fluids, etc.) is crucial in this regard (Women's College Hospital, 2017). However, patient characteristics, ED crowding, and other external factors may cause disparities in care delivery. Analyzing these factors and the timing of patient flow may reveal bottlenecks that prevent timely delivery of care, which can then provide the most cost-effective areas for administrators to focus on redesigning. **The purpose of the present study is to determine the covariates that affect the transition times between states in the ED.**

2 Background

In this section, I describe relevant relevant literature (Section 2.1) and then provide an overview of the statistical approaches for multi-state modelling (Section 2.2).

2.1 Similar Studies

The papers listed below use some type of modelling to analyze ED flow. I briefly describe the studies and findings in order to provide an overview of previous work that has been completed in this field.

1. **Emergency Department Crowding Is Associated With Delayed Antibiotics for Sepsis**

   Peltan et al. 2018

   DOI: https://doi.org/10.1016/j.annemergmed.2018.10.007

   Peltan et al. (2018) built a multi-state model with 5 transition states to analyze time to treatment with antibiotics for patients presenting to the ED with sepsis. The intermediate states included ED arrival, placement in room, clinician assessment and diagnostic data collection, with the only terminal state being antibiotic initiation. The study used data from 4 Utah EDs, including all adult patients presenting with sepsis. Their analysis revealed that while patient characteristics did not clearly influence door-to-antibiotic time, ED crowding was consistently associated with slower antibiotic initiation. These longer wait times were found to be a result of delayed initial patient assessment, rather than delayed antibiotic initiation after patient assessment.

2. **Multi-state model of the patient flow process in the pediatric emergency department**

   Liu et al. 2019

   DOI: https://doi.org/10.1371/journal.pone.0219514

   Liu et al. (2019) considered a multi-state model with seven states to better understand the flow of pediatric patients in pediatric emergency department. The study had 75,591 patients who presented to Nationwide Children's Hospital in Columbus, Ohio during one year (March 2016 to February 2017). The authors considered the states of Registration (state 1) and the terminal states are Left (state 2), Redirect (state 3), and Departure (state 7). Intermediate states consist of Exam Room (state 4), First Contact with Physicians (state 5) and Disposition (state 6). They allowed for six transitions among these states and used Cox proportional hazards model each state transition as a function of covariates (e.g., age, gender, acuity level, season). The results showed that some covariates were associated with each transition (acuity, season, time of day, and number of ED physicians) whereas other covariates like race were only associated with some transitions.

3. **An Alternative Formulation of Coxian Phase-type Distributions with Covariates: Application to Emergency Department Length of Stay**

   Rizk et al. 2019

   DOI: https://doi.org/10.1002/sim.8860

   Rizk et al. (2019) built a multi-state model with the aim of determining the effect of covariates on transition times between states in the ED. The states used consist of S1 (before triage), S2 (after triage, before treatment), and S3 (treatment). Rizk et al. found that patients presenting at night spend less time in states S1 and S3 and more time in S2 due to reduced business and a lack of night-shift staff. Those patients who arrive by ambulance are considered more urgent, and thus pass faster to S3, but their mean length of stay is also longer. Finally, older patients spend longer in stages S2 and S3, likely due to the fact that their medical needs are more complex than those of younger patients. Data included all patients presenting to a single ED in Ireland (Dec 2016 - Aug 2017).

4. **Frequent users of emergency departments and patient flow in Alberta and Ontario, Canada: an administrative data study**

   Chen et al. 2020

   DOI: https://doi.org/10.1186/s12913-020-05774-6

   Chen et al. (2020) investigated the impact of covariates on six ED transition times for adult high system users (HSU, top 10% of ED users). The intermediate states included start, physician initial assessment (PIA), disposition decision, with the absorbing states being left without being seen, left against medical advice, and end. Using this framework, the authors found that HSUs had "shorter times between start and PIA but had longer times to disposition decision and to end of the ED presentation than the control group." Data for this study was taken from the National Ambulatory Care Reporting System (NACRS, 2011-2016, EDs in Alberta & Ontario).

5. **Quantifying Dynamic Flow of Emergency Department (ED) Patient Managements: A Multistate Model Approach**

   Chaou et al. 2020

   DOI: https://doi.org/10.1155/2020/2059379

   Chaou et al. (2020) used a multi-state model approach to analyze the factors associated with various ED transition times. Intermediate states included triage, physician management and observation, with the absorbing states admission and discharge. Data was taken from all patients presenting to a single ED in Taiwan (2013). The results indicated that patient acuity, age, and time of day were all associated with transition times. Firstly, "patients with lower acuity go home more quickly but have to wait longer for physicians and admission beds." Older patients are seen more quickly, but spent more time waiting for discharge. Finally, patients arriving at night wait longer to be seen, and are admitted to the hospital more often in the afternoon, as beds are freed up by day staff.

6. **Evaluating the transitions in care for children presenting with acute asthma to EDs: a retrospective cohort study**

   Kroetch et al. 2021

   DOI: https://doi.org/10.1186/s12873-021-00550-z

   Kroetch et al. (2021) have produced a study very similar to our own. They built a 4-stage multi-state model to analyze the flow of pediatric patients presenting with asthma through the ED. The intermediate states used include triage, physician initial assessment and disposition decision, and the terminal state was ED departure. Factors found to influence patient flow were mode of arrival, acuity level, and ED location (rural or urban). However, few factors were found to influence transition times from PIA to disposition decision, indicating more uniform management decisions. Data for this study came from all EDs in Alberta (2019).

7. **Estimating Emergency Room Wait Times In Changepoint Weibull Hazard Model**

   Nguyen 2015

   DOI: https://www.wku.edu/mae/documents/erwaittimes.pdf (not published, looks more like a thesis paper or senior research project)

   Nguyen (2015) used survival analysis (without building a multi-state model) to analyze the factors associated with longer ED wait times until physician initial assessment. The analysis used data from several EDs in the US that are a part of the National Hospital Ambulatory Medical Care Survey. All patients aged 15-65 presenting in the year 2010 were included. Nguyen found that the factors associated with longer ED wait times include "female, Medicare/Medicaid insurance, low income, non-ambulance arrival, afternoon shift, and moderate urgency."

8. **Predicting Length of Stay among Patients Discharged from the Emergency Department—Using an Accelerated Failure Time Model**

   Chaou et al. 2017

   DOI: https://dx.doi.org/10.1371%2Fjournal.pone.0165756

   Chaou et al. (2017) used survival analysis (without building a multi-state model) to analyze the factors associated with overall ED length of stay (from admission to discharge). Data was taken from all patients presenting to a single ED in Taiwan (2013). The factors that were associated with longer ED lengths of stay were "increased age, higher acuity level, transferred patients, obtained X-rays, the patients obtaining CTs or laboratory tests, a consultation provided, an observation provided, critical condition declared, and day-shift arrival." Conversely, shorter length of stay was associated with "male gender, weekend arrival, whether the patient obtained an EKG, and adult non-trauma patients."

Although the studies mentioned above contain many similar and relevant elements to the planned approach, none have investigated substance misuse. Additionally, a majority of these studies did not include ED crowding as a covariate. These things being considered, it is clear that a gap exists in the literature.

2.2 A Brief Introduction to Multi-state Models

In the most general sense, multi-state models are mathematical and graphical representations of a *process* in time (Hougaard, 1999). The framework of multi-state models is that of a finite number of mutually exclusive states that an agent may occupy. This framework, also known as the "state structure," is usually pre-determined by the researcher, and the events of interest are the transitions between these states. Agents begin in a particular state, and then stochastically move between available states. Occurrence of one particular event/transition may influence the probabilities of another event occurring. Some multi-state models contain a final "absorbing state," which does not allow the agent to leave (ex. death). States can represent any number of discrete conditions held/occupied by an agent, such as operational/degraded/failure in engineering (Castet and Saleh, 2010), good weather/bad weather in meteorology (Li et al., 2012) or unmarried/married/widowed in sociology (Schwartz and Mare, 2012), and many more. Ultimately, the state structure is flexible and should be chosen such that it is informative in regards to the research question. A famous example of a multi-state model is the illness-death epidemiology model in medicine, which can be represented graphically in Figure 2:

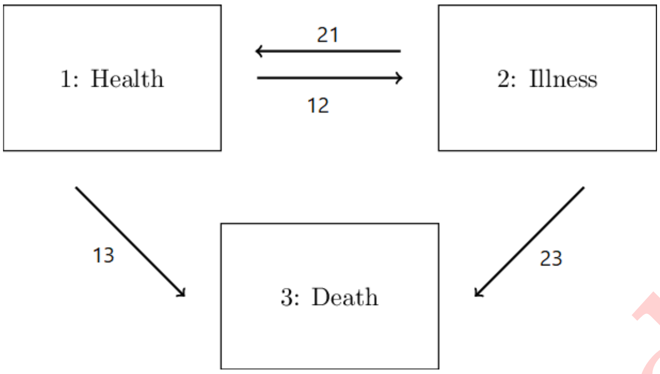

Figure 2: The illness-death model, a famous example of a multi-state model. In this case, the beginning state is "health", the intermediate state is "illness", and the absorbing state is "death." Other multi-state models may have more than three states, and can be connected in many different ways, including bi-directional travel ("non-progressive") and self-pointing loops. (Source: https://www.researchgate.net/figure/The-Illness-Death-Model_fig2_341785920.)

Each transition between states in the illness-death model above has an associated "transition probability" (assuming discrete time). Each time step, the transition probability is the probability that the particular transition will occur. For example, assume that we are doing an analysis of the illness-death model, using 1 day as the discrete time step size (in reality, the size of the time step can be any size, so long as it is specified in advance by the researcher). Also suppose that the 1-2 transition from health to illness has an associated transition probability of 0.3. This means that every day, there is a 30% chance that a particular person will become ill. In continuous time models, these discrete time probabilities are collapsed to "transition intensities" or "hazards", which are the instantaneous risk of the transition occurring.

There are two main ways in which multi-state models are used: to make predictions based on certain initial conditions, and to determine the effects of confounding variables on the transition probabilities.

In the first case, study data (observational or experimental) is used to determine transition probabilities, which are entered into a matrix representing the state structure. A set of differential equations and certain initial conditions then facilitates predictive modeling of system dynamics. Following with the illness-death example, previous research could have estimated the transition probabilities between the states, and thus a variety of potential scenarios can be explored using differential equations and the proper computer software. For example, researchers might ask: how will the system behave long-term? Is there a steady state, or does the system oscillate? Such approaches can inform policy formation and other such decisions.

In the second case, the transition probabilities have not yet been estimated. In order to estimate them, functions can be fit to relevant time to event data, also known as survival data. For example, we may wish to know the rate of incidence of illness in a particular community. Assuming we could monitor the health status of all community members, observational data would reveal the times of onset of illness (since some time t=0). Then, a decaying exponential function could be fit to this data, giving the "survival function" and thus also the relevant transition probability. Such approaches can be used to predict median time to becoming healthy again for an individual after they have become ill. Often, however, we want to compare the odds of transition between individuals that differ with respect to a confounding variable. In the case of the illness-death model, estimating the transition probability (or intensity, if in continuous time) for the "illness" to "deceased" transition could give the probability of dying during the next time step, but it is also useful to determine what covariates make this transition more likely. For example, it is possible that older people have a higher chance of dying, making age a covariate. Or, maybe smoking status predisposes an individual to dying (the comparison of transition probabilities in discrete time is called the "relative risk", while the comparison of transition intensities in continuous time is called a "hazard ratio"). Such approaches can be used to identify and eliminate harmful confounding variables to extend (or reduce) the median time to a certain event (ex. advising patients to stop smoking to increase lifespan, etc.).

2.2.1 Survival Analysis

The simplest multi-state model would be a system of two states with a single one-way transition between them. In the case of such a system, there is only one possible event: a one-time, stochastic transition between states 1 & 2. Analyses of these kinds of data are typically referred to as "survival analysis". Survival analysis is the examination of "time-to-event" data, i.e. how long it takes for something to occur. The most basic "survival function" (function that describes time-to-event data) is the Kaplan-Meier (KM) curve, which is both an estimate and a graphical depiction/summary of data (Figure 3). The x-axis shows time, and the y-axis the proportion of individuals who have not yet experienced the event (i.e., transitioned to the next state). The KM curve is a step-wise function, but when there are many individuals involved, it may look more like a smooth curve.

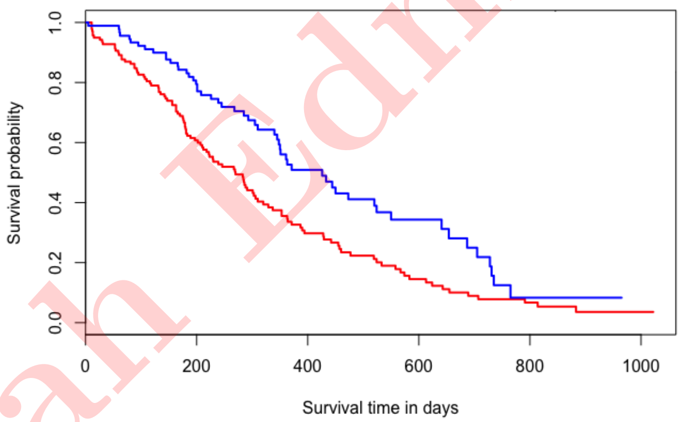

Figure 3: An example of a Kaplan-Meier survival curve. KM curves are good for graphically displaying survival data, and for estimating median transition time. (Source: https://felixfan.github.io/Kaplan-Meier-Curves/.)

Data may also be "censored," meaning that the exact time of the event occurrence is unknown. The two most common types of censoring are right censoring and interval censoring. In the case of right censoring, we know that the time of event occurrence is greater than some value. This can happen, for example, if we are following people at risk for heart attack, but the study period is ended before all the participants have experienced a heart attack. We know that these individuals might well experience a heart attack after the study ends, but we do not have the exact time. In the case of interval censoring, we know that the time of occurrence is between two values. This is common in situations involving clinical check-ups. We know the patient developed the disease state at some point between the last and current check-up, but we do not know exactly when in this time period the transition occurred. While censored data is missing some critical information, it can still be useful to include it in our analysis. While we might not know the exact time, we know that a certain individual survived *at least* this long (or between two known times), which is still informative.

The usual way in which KM curves are used in survival analysis is to determine the probability that an individual patient will survive past a particular time t. KM curves can also be built for two groups that have been divided based on some other categorical variable. Then, these curves can be compared using the “log-rank test,” which determines if the two curves are significantly different from each other or not.

A drawback of KM estimates is that they are not parameterized. This is a drawback because we are unable to see how the survival probabilities are a function of covariates. Plotting KM curves for different categories limits the understanding of the effect of categorical and continuous covariates.

Because we are more interested in the influence of covariates on transition intensities (in continuous time) between states, Cox Proportional Hazard (CPH) models are an important approach to consider (Cox, 1972; Kumar and Klefsjö, 1994). CPH models are regression-style models used for analyzing time-to-event data in the context of survival analysis. These models assume that the transition process is Markovian (i.e. that the current transition depends only on the current state, not previous states), but unlike Markov chains, CPH models cannot explicitly determine the transition intensities/probabilities for the transitions between states. This is because CPH models are semi-parametric, meaning that some parts of the underlying mathematics are parameterized, and some are not. While the covariates are explicitly parameterized, the hazard function (rate of decrease of the curve) is not explicitly defined, which means that it is allowed to change over time (in this sense, CPH models are “non-homogeneous Markov extension models” (Hougaard, 1999)). Being only semi-parametric is beneficial as it is often more realistic (than, say, a simple decaying exponential function), but as a result, the CPH model does not give an estimate of the instantaneous hazard (a metric similar to the transition probabilities of Markov chains, as previously discussed). Instead, CPH models only allow us to look at the hazard ratios, which tell us how much more likely one individual is to transition to the next state compared to another individual based on a differing covariate.

In addition to the Markov assumption, CPH models make one other assumption, which is the “proportional hazards assumption.” This assumption is that groups of observations (i.e. those created by separation of individuals based on a confounding categorical variable) have proportional hazards, meaning that their hazard curves do not cross, and are instead reasonably parallel (STHDA). In other words, the assumption is that the hazards of two population subgroups do not change in different ways (the hazard is allowed to change, but only in the same way for both groups). This assumption can be checked using log-log plots and Schoenfeld’s test. The assumption is considered true if, on a log-log plot, the lines do not intersect. Schoenfeld’s test involves a null hypothesis of proportional hazards, so a large p-value (above 0.05) confirms the assumption (STHDA).

CPH models allow the incorporation of multiple possible covariates. Adding covariates to the model should influence the estimate of the baseline hazard (or the standard error of these estimates) if the covariate is indeed predictive. After creating several CPH models of the same data, these models can be compared using Akaike’s information criterion (AIC), or the likelihood ratio test (if the models are nested).

2.2.2 Software

Theoretically, a variety of multi-state models can be implemented using any statistical software, but R is certainly the most extendable. Common packages in R for modeling multi-state processes include:

- `msm` (+ `tdc.msm`) $\longrightarrow$ This package includes “functions for fitting continuous-time Markov and hidden Markov multi-state models to longitudinal data" (https://cran.r-project.org/web/packages/msm/msm.pdf). This package is preferable, as it computes all HR simultaneously, instead of one transition at a time.

- `mstate` ⟶ This package includes "functions for data preparation, descriptives, hazard estimation and prediction with Aalen-Johansen or simulation in competing risks and multi-state models" (https://cran.r-project.org/web/packages/mstate/mstate.pdf).
- `survival` ⟶ This package includes "the core survival analysis routines, including definition of Surv objects, Kaplan-Meier and Aalen-Johansen (multi-state) curves, Cox models, and parametric accelerated failure time models" (https://cran.r-project.org/web/packages/survival/survival.pdf). This package is the most commonly used, and is perfect if you are able to maintain the Markov assumption (transition probabilities depend only on the current state).

3 Methods

In this section, I first describe the sources of the data used in this study (Section 3.1), how the substance misuse patient population was classified (Section 3.2), and descriptions of all of the relevant variables (Section 3.3). I end this section with an explanation of the statistical approach taken to the multi-state model (Section 3.4).

3.1 Data Sources

The National Ambulatory Care Reporting System (NACRS) is a collated dataset created by the Canadian Institute for Health Information (CIHI, 2020). All emergency departments in Alberta collect data on patients presenting to the ED, which includes characteristics of their ED presentations. Each month, these data files are submitted to CIHI, that creates a data product for use. The dataset under consideration in this analysis contains the CIHI NACRS data from April 1, 2019 through March 31, 2020. This means that it captures all Albertans (i.e., both adults and children) who presented to any Albertan ED for any reason during this time period.

Additional variables (those concerning rural character of patient residence and neighbourhood income) were derived from NACRS patient postal codes using the Pampalon Index (Pampalon et al., 2009). The Pampalon Index is a database that includes a list of dissemination areas, alongside their associated neighbourhood income and placement along the rural-urban continuum. Using patient postal codes, we can refer to the Pampalon Index in order to determine these two additional metrics for each presentation.

One additional variable relating to patient comorbidities was extracted from another CIHI database called the Discharge Abstract Database (DAD). This source contains information relating to hospital discharges. Looking back on 2 years of both NACRS and DAD data, Alberta Health Services (AHS) was able to assign Charlson comorbidity scores (discussed below) for every presentation.

3.2 Case Definition

Upon presentation, the severity of each patient's condition is assessed by a nurse or other trained healthcare provider ("triage"). Later, the information recorded by this worker is used to assign to the patient up to 10 diagnostic codes that describe their condition upon presenting. The coding scheme currently in use in Alberta is called the International Statistical Classification of Diseases and Related Health Problems, 10th Revision, Canada (ICD-10-CA) (CIHI, 2018). These codes were used to identify patients of interest. The patient subset under consideration in this analysis are those individuals presenting with substance misuse-related concerns. The appropriate ICD-10-CA codes for identifying this patient subset are F10.0 to F19.9 & T36.0 to T50.9 (Di Rico et al., 2018). These F codes encompass individuals with "mental and behavioural disorders due to psychoactive substance use", and the T codes included individuals with "sequelae of poisoning by drugs, medicaments and biological substances" (https://icd.who.int/browse10/2010/en#/). If a presenting patient had even one relevant code in any of the 10 available diagnostic fields, they were included in this analysis.

3.3 Variable Description

Several basic demographic variables are recorded for each patient presenting to an ED. These include items such as age, gender, and postal code of patient's residence. Age is recorded in whole years at the time that the patient presents. Gender is recorded as either male, female, or other. Alberta is divided geographically into 5 health zones for the delivery of health services: North, Edmonton, Central, Calgary and South (Figure 4). The postal code of a patient's residence is geocoded to determine which zone the patient resides.

Figure 4: Alberta's five health zones, as per Alberta Health Services.
(Source: https://www.albertanetcare.ca/learningcentre/AHSResources.htm.)

Postal codes can also be linked to other demographic data, such as neighbourhood income and rural character of the patient's residence. Both of these are determined using the Pampalon Index. The first of these can be used as a coarse proxy for the patient's socioeconomic status (SES). This is a useful measure, as SES has been proven to have significant health implications (Braveman, 2014). Secondly, the rural character of a settlement is ranked on the "Rural-Urban Continuum" (Alberta Health Services, 2018b). Both the population density of the settlement and its distance from urban centres and services are considered in ranking. The types of settlement are: metropolis (i.e., Calgary & Edmonton), moderate metropolis influence (areas immediately surrounding Calgary and Edmonton), urban (i.e., Grand Prairie, Fort McMurray, Red Deer, Lethbridge, and Medicine Hat), moderate urban influence (areas immediately surrounding the 5 urban areas), rural centre area (population size >10,000 but <25,000 people), rural (population size <10,000 people, and up to 200km away from a metro or urban centre), and rural remote (anywhere further than 200km away from a metro or urban centre).

Additional data relating to the patient's condition upon presenting to the ED is also extracted. This information is stored in the Discharge Abstract Database (also maintained by CIHI), and can be used to calculate patient comorbidities using the Charlson index (Charlson et al., 1987). The Charlson index of comorbidity was developed in 1987 as a method of classifying certain comorbid conditions that could affect survival and mortality for longitudinal studies. Patients are assigned a numerical score of 1, 2, 3 or 6 for each comorbidity they have, and these are then summed to get their overall Charlson index score. Comorbid conditions that score low on the Charlson index include things such as myocardial infarct, dementia, and diabetes, and conditions that score higher include diseases such as liver disease, metastatic cancer, and acquired immunodeficiency syndrome (AIDS).

The mode of arrival of the patient and the type of ED are also recorded. These modes of arrival include: arrival on foot, by ambulance, by air (e.g., emergency helicopter) or some combination of these. In regards to ED type, AHS recognizes eight, and they depend on the variety of services available at that facility. These groups include: Tertiary referral (large, extensive hospitals in Calgary and Edmonton), Regional referral (sizable hospitals in municipalities surrounding Calgary and Edmonton), Urgent Care centre (ie. "Urgent Care Services"), Community with less than 600 inpatients, Community with specialty services and greater than 600 inpatients, Community with specialty services and less than 5,000 inpatients, Community Ambulatory, and Community Ambulatory Moderate. In order to simplify these ED types and make them more easily understandable, they were further categorized into the following levels: Tertiary, Regional, Community, and Urgent Care.

All presenting patients are triaged soon after entering the ED, and their "triage level" is recorded. The Canadian Triage and Acuity Scale (CTAS) is a nationally recognized system of defining the severity of an injury (Beveridge et al., 1998). A value of 1 on this scale is also called "Resuscitation", and is assigned to the most urgent and severe cases (i.e., imminent threat of deterioration). The second highest code is referred to as "Emergent", and is assigned to conditions that represent a potential threat to life. Triage level 3 is called "Urgent", and is assigned to cases that could potentially progress into a more serious problem. The second lowest triage level is 4, or "Less Urgent", and it is assigned to patients whose conditions would benefit from intervention within 1-2 hours. The least severe triage level is 5, or "Non-Urgent." Patients triaged with level 5 have only minor symptoms, and will not deteriorate in the near future.

Aside from demographic and health information, dates and times are recorded for each major point along the ED "track", allowing for the analysis of patient flow through the ED. Of these times, those for when the patient physically left the ED were separated based on disposition decision, as there are multiple ways in which a patient may leave the ED. There are 20 possible disposition codes as per AHS, 16 of which appeared in our dataset (Alberta Health Services, 2018a). The meaning of these codes can be found in Appendix C.

The amount of crowding an ED is experiencing in any given hour can be estimated using several methods, all of which use other previously recorded variables. One such method uses the total number of presentations to that particular ED in each hour. Another uses the proportion of patients LWBS per day. The metric chosen for the present analysis is average time from arrival to PIA. This metric was calculated using the entire NACRS dataset for every hour throughout the year, separated by individual EDs. If this time was over 1 hour, that ED was labeled "Crowded" for that hour, and if it was under 1 hour, it was labeled as "Not crowded".

3.4 Statistical Analysis

3.4.1 Variable Grouping

Some variables have been re-categorized to facilitate interpretation and modelling. For instance, patient municipality levels were combined into 'metropolis', 'urban', 'rural', and 'remote'. Patient neighbourhood income was combined into 'Below $25,000', 'Between $25,000 - $50,000' and 'Above $50,000'. Diagnostic codes were grouped into 'alcohol' (all F10 codes), 'methamphetamines' (all F15 codes & T43.6), 'opioids' (all F11 & T40 codes), and 'other' (all other codes in current subset). If patients had codes belonging to multiple groups, the priority was 'alcohol' > 'opioids' > 'methamphetamines'. Charlson index scores were coded as either '0' or '1+'. Days of the week were grouped as either 'Weekday' or 'Weekend'. Time of day was either 'Day' (0800-1559), 'Evening' (1600-2359), or 'Night' (0000-0759). Triage codes were not grouped. ED crowding was grouped as described in the previous section. Age was the only continuous numeric variable; it was divided by 10 to permit easier numerical optimization. While not a covariate, disposition code was also grouped so that cases could be assigned to the appropriate model state. These codes were grouped into the following categories: discharged (16,17), transferred (8,9,30,40,90), admitted (6,7,12,14), LWBS (61), LAMA (62,63,64) and died (72).

3.4.2 Data Preparation and Exploratory Data Analysis

Data cleaning was performed prior to analysis. Non-ED visits, invalid patient IDs and duplicate presentations were removed. Missing variables coded as 999 as well as other non-allowed/impossible values were switched to NA. Genders reported other than male and female were switched to NA (n = 6 removed). Individuals receiving "died" or "LWBS" disposition codes were removed (n = 39 and 7, respectively). Individuals arriving to the ED via air ambulance were also removed (n = 251 removed). Presentations where the total length of stay was over 168 hours (1 week) were taken to be data entry errors, and were removed (18 total). Certain categorical variables were aggregated into smaller groups, as discussed above.

Summary statistics such as percentages, mean, median, minimum and maximum were used to summarize demographic data relating to individual ED presentations, as well as data relating to each ED visit and ED flow (i.e., ED type, mode of arrival). In order to calculate transition times, the difference was determined between successive time points. For example, patients are first registered and then triaged upon arrival to the ED. The transition time can then be calculated based on the next time point, which is PIA. (However, for some reason or another, a patient may be triaged before they are registered. Therefore, the first of these was used in calculations; termed "start".) This same process can be used to find the transition time between PIA and disposition decision, as well as disposition decision and time of leaving the ED. Each of these transition times were separated by ED type and visualized using box plots.

In addition to flow, ED presentation times (the first of triage time or arrival time) can also be used to track the number of ED presentations through time (e.g., hours of the day, days of the week). This information highlights the times during which people are more likely to present to the ED with substance-misuse related concerns. The average number of presentations occurring per hour was calculated by summing the number of presentations throughout the entire study period that occurred during each hour, and then dividing by the number of days (365). The average number of presentations occurring per day of the week and month of the year were calculated in a similar manner. To find the average number of presentations per day of the week, the number of presentations that occurred during each day of the week were summed and then divided by the number of weeks in the study period (52). To find the average number of presentations per month of the year, the number of presentations that occurred during each month of the year were summed (division was not necessary in this case, since each month only occurs once throughout the study period).

Statistical software R version 3.6.1 was used to complete the analysis (R Foundation for Statistical Computing, Vienna, Austria; URL: https://www.R-project.org/). Histograms, box plots, Kaplan-Meier curves, forest plots and bar plots were also used where applicable.

3.4.3 Multi-state Modelling

In order to facilitate multi-state modelling, the data required additional cleaning. Cases that were missing all relevant transition times were removed. If cases did not contain any sequential times, or had times that were out of order were also removed. Data was then transformed from "wide" format (one row per case) to "long" format (one row per transition, per case). If consecutive times were identical, 1 second was added to the later time (this was done to prevent compilation errors in R). Factor-type covariates were then re-leveled to reflected the appropriate reference group, and any unused levels were dropped. Separate multi-state models were then fit for each covariate separately, as well as all covariates simultaneously. All modelling was performed in R's 'msm' package.

Several steps were performed in order to fit each model. First, a matrix of allowable transitions was constructed and then passed to `crudeinits.msm()` in order to obtain a rough estimate of the transition intensity matrix (Table 1). Once these initial values had been calculated, the long format data was passed to `msm()`. Options included in the model call were: `exacttimes = TRUE` and `control=list(reltol = 1e-12, maxit = 1000)`.

Table 1: Matrix of allowed transitions (this is what was passed to `crudeinits.msm()`).

	State To						
State From	*1*	*2*	*3*	*4*	*5*	*6*	*7*
1 Start	0	0.5	0	0	0	0	0
2 PIA	0	0	0.5	0.5	0	0	0.5
3 Discharge Disp.	0	0	0	0	0	0	0
4 Adm./Tran. Disp.	0	0	0	0	0.5	0.5	0
5 Admitted	0	0	0	0	0	0	0
6 Transferred	0	0	0	0	0	0	0
7 LAMA	0	0	0	0	0	0	0

Once a full model using all hypothesized covariates had been fitted, model reduction was performed. This was done by identifying the widest hazard ratio confidence interval for each transition that included 1, and then removing it. This was done for all transitions simultaneously, unless there were no confidence intervals left that included 1. A total of 4 rounds of model reduction were performed, and then each model was compared for best fit using Akaike's Information Criterion (AIC). All results described below refer to this best reduced model.

If at any point patient counts were small numbers, these categories were not shown in order to maintain patient anonymity.

4 Results

In this section, I begin with a basic demographic summary of patient characteristics, (Section 4.1), as well as ED presentation characteristics (Section 4.2). Next, I give summary of the transition time data (Section 4.3) and a graphical representation of some of the trends in this time data (Section 4.4). Most importantly, I then provide tables and forest plots of the hazard ratios generated from multi-state modelling (Section 4.5). Lastly, I provide the results from model reduction (Section 4.6).

4.1 Demographics

After cleaning the data, 2,302,147 separate presentations were available for analysis. Of these, 74,455 presentations were made to all Alberta EDs for substance misuse-related concerns. These 74,455 substance misuse presentations were made by 40,995 unique patients. As seen in Table 2, substantially more presentations were made by males than by females (61% & 39%, respectively). The majority of these presentations were made by individuals living in health zones Edmonton and Calgary (33% & 31%), which makes sense, given their relative population size. Figure 5 shows the distribution of ages among ED presentations. Individuals aged 25-29 were the most numerous category (10,697; 14%).

Table 2: Demographic characteristics of presentations for substance misuse to emergency departments in Alberta from April 1, 2019, to March 31, 2020.

Variable		**Count**	**Percentage**
Total		74,455	
Age (years)			
	Mean (SD)	37.0	(15.1)
Gender			
	Male	45,449	61.0
	Female	29,000	38.9
Charlson			
	0	54,792	73.6
	1+	19,663	26.4
Health Zone			
	North	10,512	14.1
	Edmonton	24,609	33.1
	Central	8,142	10.9
	Calgary	23,273	31.3
	South	6,417	8.6
	Missing	1,502	2.0

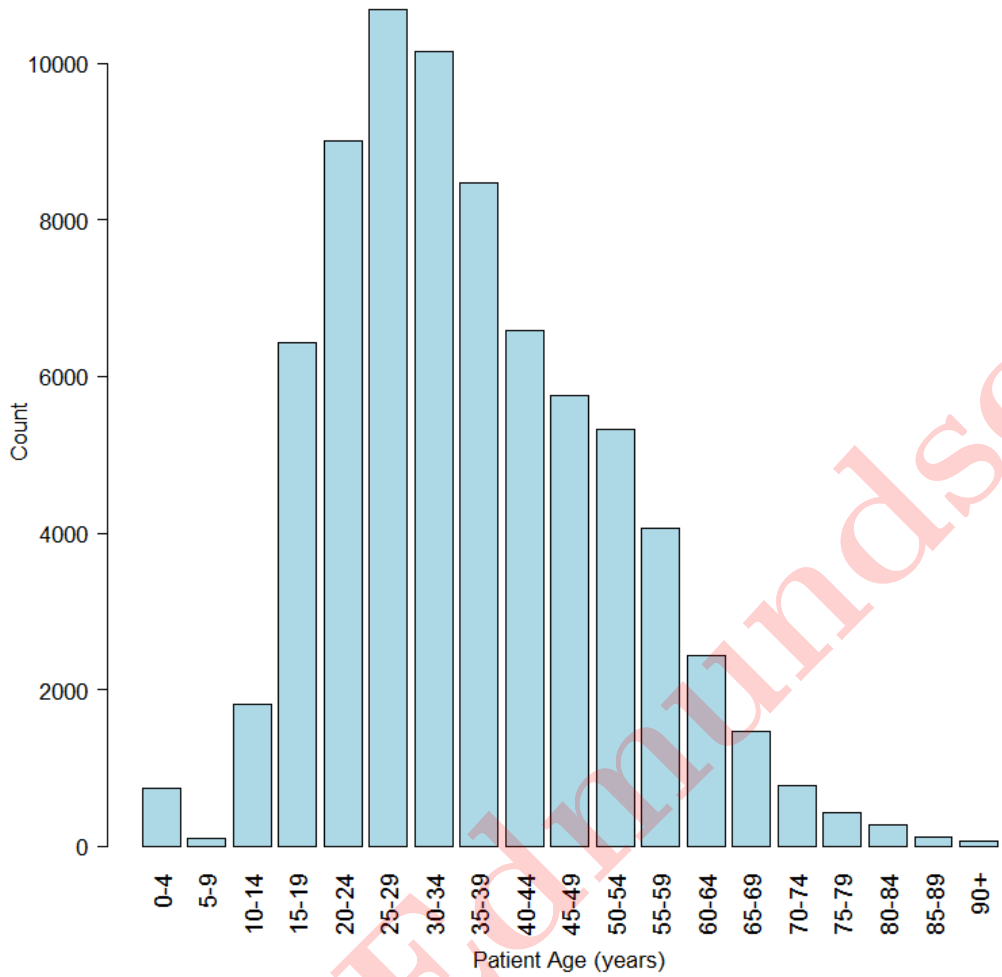

Figure 5: Age distribution of presentations for substance misuse to all Alberta EDs, from April 1, 2019 through March 31, 2020.

Table 3 shows the Pampalon Index variables. In regards to patient neighbourhood income, the middle income group ($25,000 - $50,000) was more highly represented in the current population of study, with 42% of all cases. Also, the majority of presentations were made by individuals living in metropolitan areas (57%), with a substantial minority coming from rural areas (22%).

Table 3: Pampalon variables for all substance misuse presentations to emergency departments in Alberta from April 1, 2019, to March 31, 2020.

Variable		Count	Percentage
Total		74,455	
Neighbourhood Income			
	Below $25,000	6,699	9.0
	$25,000 - $50,000	31,189	41.9
	Above $50,000	31,956	42.9
Location of Patient Residence			
	Metro	42,234	56.7
	Rural	16,134	21.7
	Urban	8,537	11.5
	Remote	2,939	3.9

4.2 ED Presentation Characteristics

Table 4 provides the characteristics of the ED presentations including the data about the mode of arrival, Charlson index score, ED type, and the most common diagnosis codes. Individuals more often presented to regional EDs, as opposed to larger, tertiary ones (40% vs. 28%). Patients presented fairly evenly throughout the months of the year, and around half arrived by ambulance (48%). Such a significant number of individuals arriving by ambulance is understandable, given that the vast majority of presentations were triaged as either "Urgent" or "Emergent" (81.8%; CTAS levels 1-3). Despite the urgency of the triage scores, the majority of these substance misuse patients were discharged (66%).

The most common ICD-10 codes were those representing alcohol misuse (49%), although diagnostic codes did vary to a reasonable extent. The fourth most common diagnostic code was "Medical observation for suspected cardiovascular diseases," although - as seen in Figure 6 - only a small number of patients scored higher than a 1 in the Charlson comorbidity index (11%). Also quite common (5th most) in the present population is homelessness (at least 12%). It is worthwhile to note, however, that the ICD code for homelessness may not be reliably recorded, so the true value may be larger than 12%. Homelessness in Canada has been estimated to be around 5%, meaning that homeless individuals are presenting to the ED with substance misuse concerns at a higher relative rate than non-homeless individuals (Cousins, 2020). These figures suggest that increased support is needed for homeless individuals struggling with substance misuse.

Table 4: Information relating to ED visit for all substance misuse presentations to emergency departments in Alberta from April 1, 2019, to March 31, 2020, after data cleaning.

Variable		Count	Percentage
Total		74,455	
Arrival Mode			
	No Ambulance	38,821	52.1
	Ambulance	35,541	47.7
Day of the Week			
	Weekday	51,529	69.2
	Weekend	22,926	30.8
Time of Day			
	Day (0800 - 1559)	23,919	32.1
	Evening (1600 - 2359)	31,244	42.0
	Night (0000 - 0759)	19,292	25.9
ED Type			
	Regional	29,738	39.9
	Tertiary	21,098	28.3
	Community	19,719	26.5
	Urgent Care Centre	3,813	5.1
Triage Level			
	Resuscitation (1)	2,356	3.2
	Emergent (2)	26,584	35.7
	Urgent (3)	31,953	42.9
	Less Urgent (4)	11,102	14.9
	Non-Urgent (5)	1,638	2.2
Most Common Diagnostic Codes			
	F10.0 Alcohol - Acute intoxication	16,321	21.9
	U98.9 Unspecified place of occurrence	14,495	19.5
	F10.1 Alcohol - Harmful Use	10,086	13.5
	Z03.5 Suspect for cardiovascular disease	8,910	12.0
	Z59.0 Homelessness	8,903	12.0
Diagnostic Code Groupings			
	Alcohol	36,780	49.4
	Methamphetamines	8,747	11.7
	Opioids	10,072	13.5
	Other	18,856	25.3
Disposition			
	Discharged	49,105	66.0
	Admitted	12,961	17.4
	Left Against Medical Advice	7,165	9.6
	Transferred	5,224	7.0
Crowding Level			
	Not Crowded	19,408	26.1
	Crowded	50,072	67.3

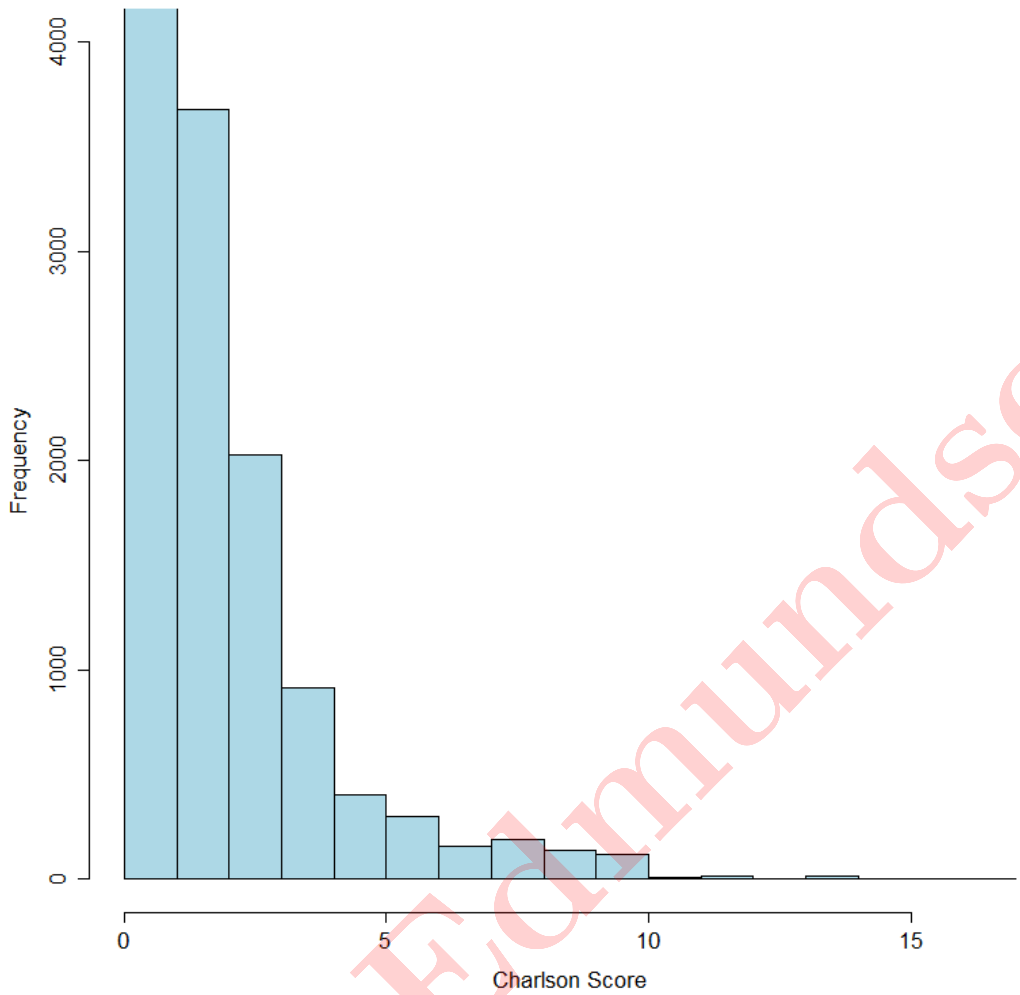

Figure 6: Charlson comorbidity index scores of all presentations to Alberta EDs with substance misuse, from April 1, 2019 through March 31, 2020. The first bin carries the most presentations by far, extending to 55,000 presentations. This bin has been cut off to better see the distribution of the other bins.

4.3 Transition Times

The key times are provided again graphically in Figure 7. Summary statistics of the times between various transitions and the total length of stay appear in Table 5. The median time that it took for a patient starting in the ED to be seen by a physician was 1h 13m (h = hour, m = minutes). The median time that it took for ED staff to collect additional patient data and for the attending physician to decide how the patient leaves the ED (i.e., time from PIA to disposition) was 4h 06m. The subsequent transition time - disposition to leaving the ED - differed based on the disposition code. The majority of the discharged patients left immediately after the physician made the disposition decision, giving a median time of 0h 0m (30,311; 99.8%). For admitted patients, the median time between disposition decision and leaving the ED (i.e., time spent waiting for an inpatient bed) was 3h 13m. Like the discharged patients, the majority of the transferred patients left the ED immediately (3,347; 88.1%). Considering the patients that chose to leave the ED against medical advice, these individuals spent a median time of 3h 05m in the ED before leaving.

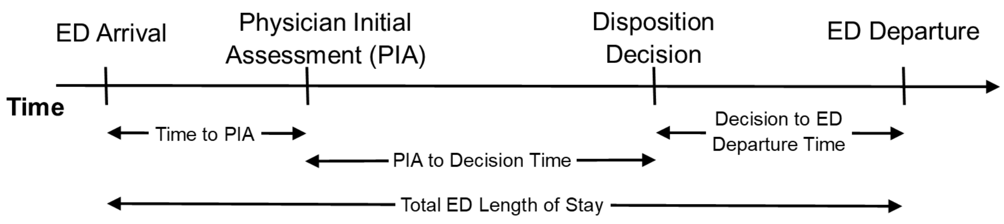

Figure 7: Important time points in the ED flow process.

When ED type was considered, community EDs had the lowest median wait time from start to PIA, and tertiary EDs had the longest (Figures 8 & 9). In terms of wait times for an inpatient bed, Community EDs had the shortest wait times from disposition to admission, and Urgent Care centres had the longest (Figures 10 & 11). Patients presenting to tertiary EDs were the most patient, in the sense that these presentations had longer start to LAMA times (Figures 12 & 13). Urgent care centres had the shortest start to LAMA times.

Table 5: Summary variables for all transition times, for all substance misuse presentations to emergency departments in Alberta from April 1, 2019, to March 31, 2020, after removing rows with incorrect time data.

Transition Time	**Count**	**1st Qu.**	**Median**	**Mean**	**3rd Qu.**	**Max.**
Overall LOS	63,226	3h 33m	6h 34m	9h 59m	12h 04m	164h 13m
Start to PIA (State 1-2)	61,165	0h 32m	1h 13m	1h 49m	2h 29m	30h 28m
PIA to Discharge Disp. (State 2-3)	43,189	1h 32m	3h 36m	5h 24m	7h 20m	113h 15m
PIA to Adm./Tran. Disp. (State 2-4)	15,763	3h 08m	5h 39m	7h 17m	9h 31m	99h 56m
Disp. to Discharge (not modelled)	29,774	0h 00m	0h 00m	0h 02m	0h 00m	135h 00m
Disp. to Admission	12,906	1h 04m	3h 16m	10h 36m	14h 32m	159h 05m
Disp. to Transfer	4,204	0h 00m	0h 00m	3h 12m	0h 00m	119h 34m
PIA to LAMA	1,417	1h 10m	2h 35m	4h 10m	5h 25m	39h 02m

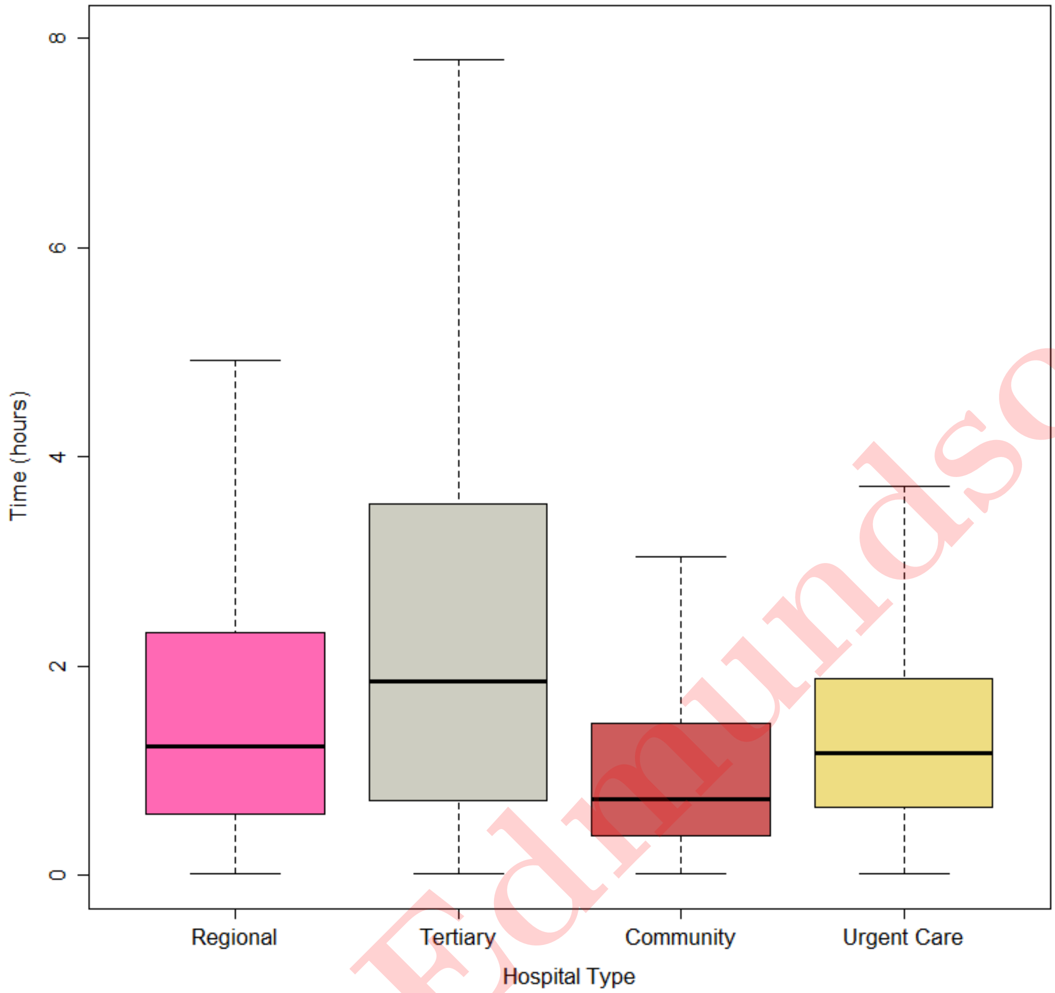

Figure 8: Box plots for the start to PIA transition time, separated by ED type. Times over 10 hours were removed.

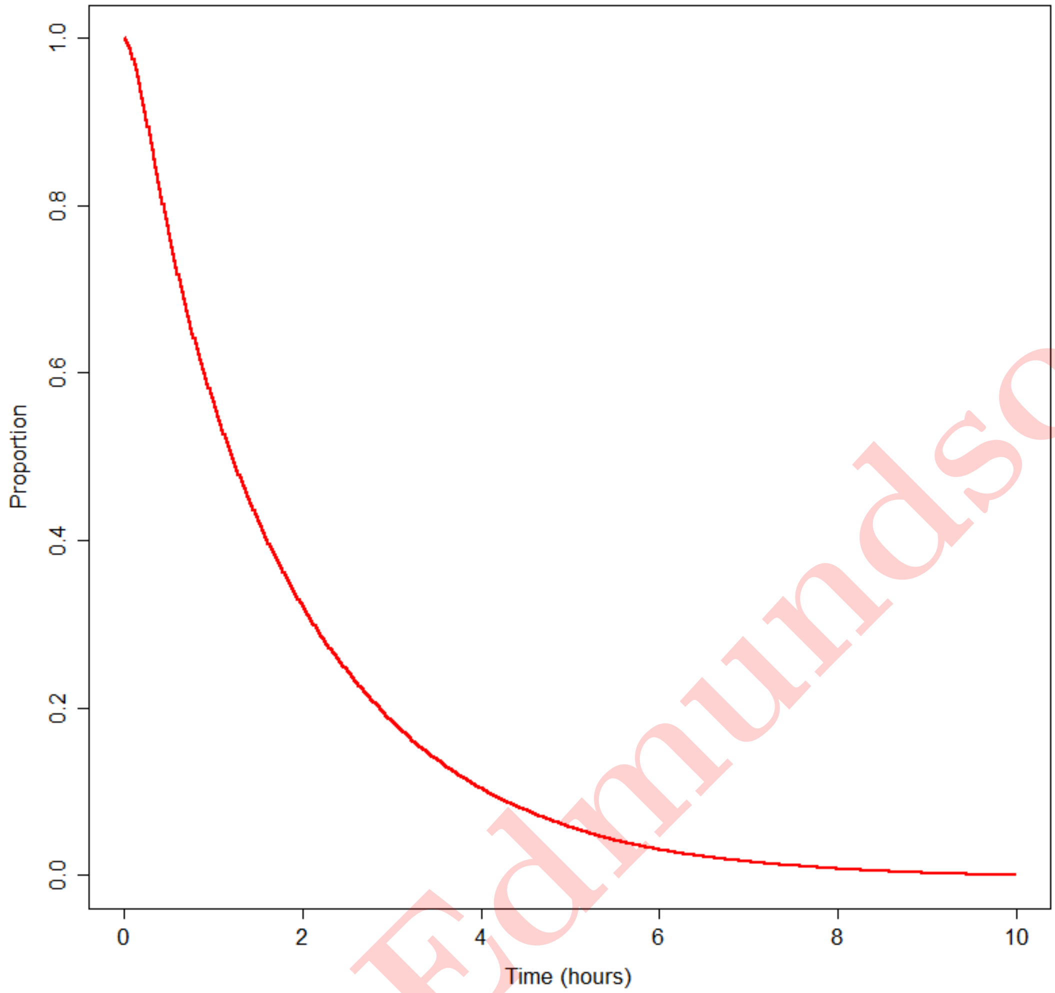

Figure 9: Kaplan-Meier curve for the start to PIA transition time. Instantaneous times (0h 00m) were removed prior to plotting.

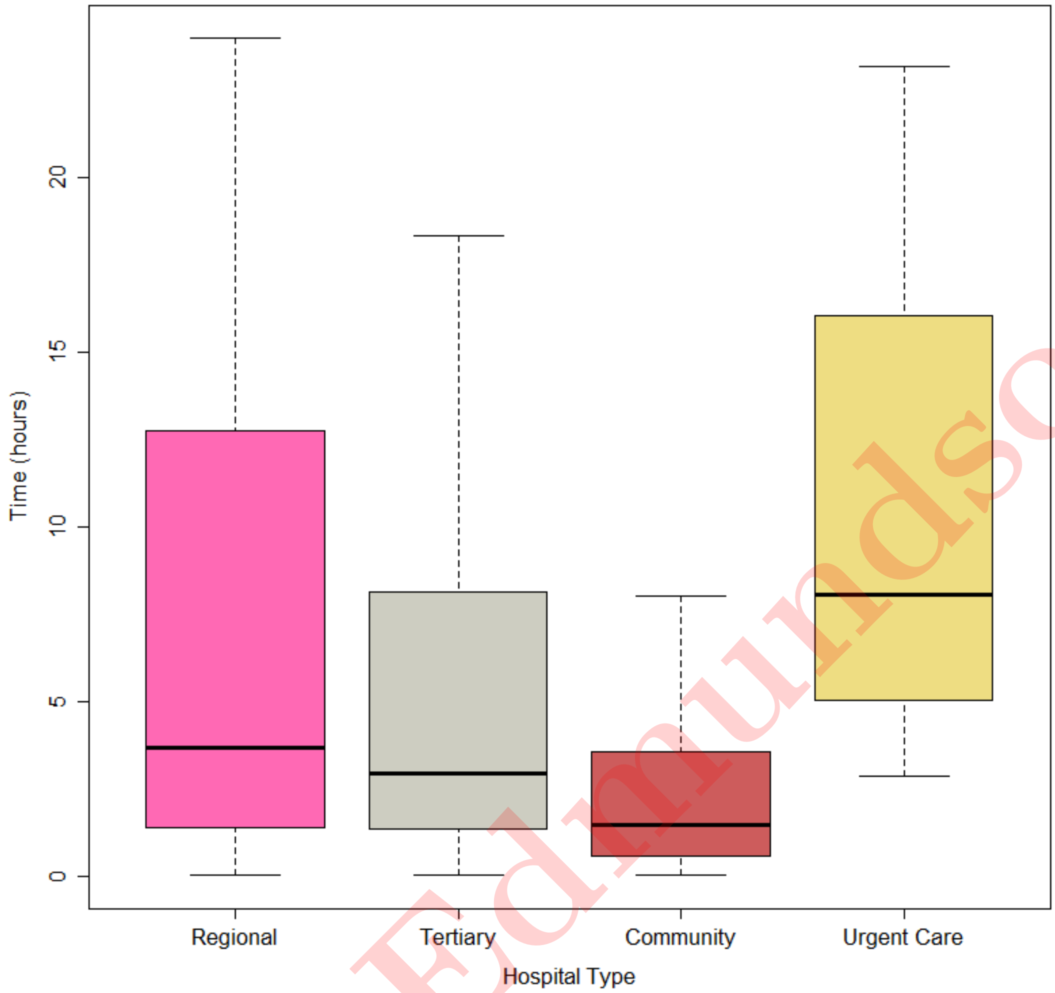

Figure 10: Box plots showing the wait times for an inpatient bed, after the decision to admit the patient has been made. Transition times have been separated by ED type. Times over 24 hours were removed.

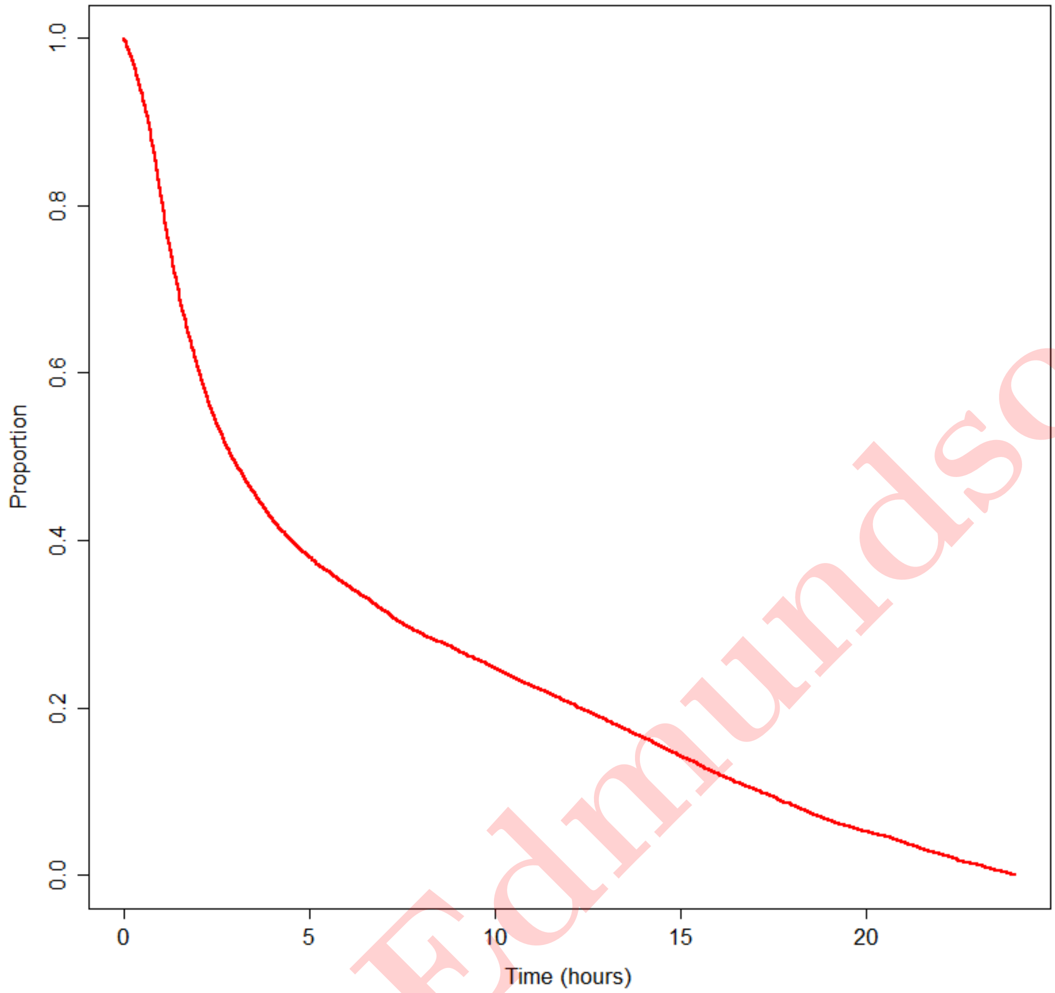

Figure 11: Kaplan-Meier curve showing the wait times for an inpatient bed, after the decision to admit the patient has been made. Instantaneous times (0h 00m) were removed prior to plotting.

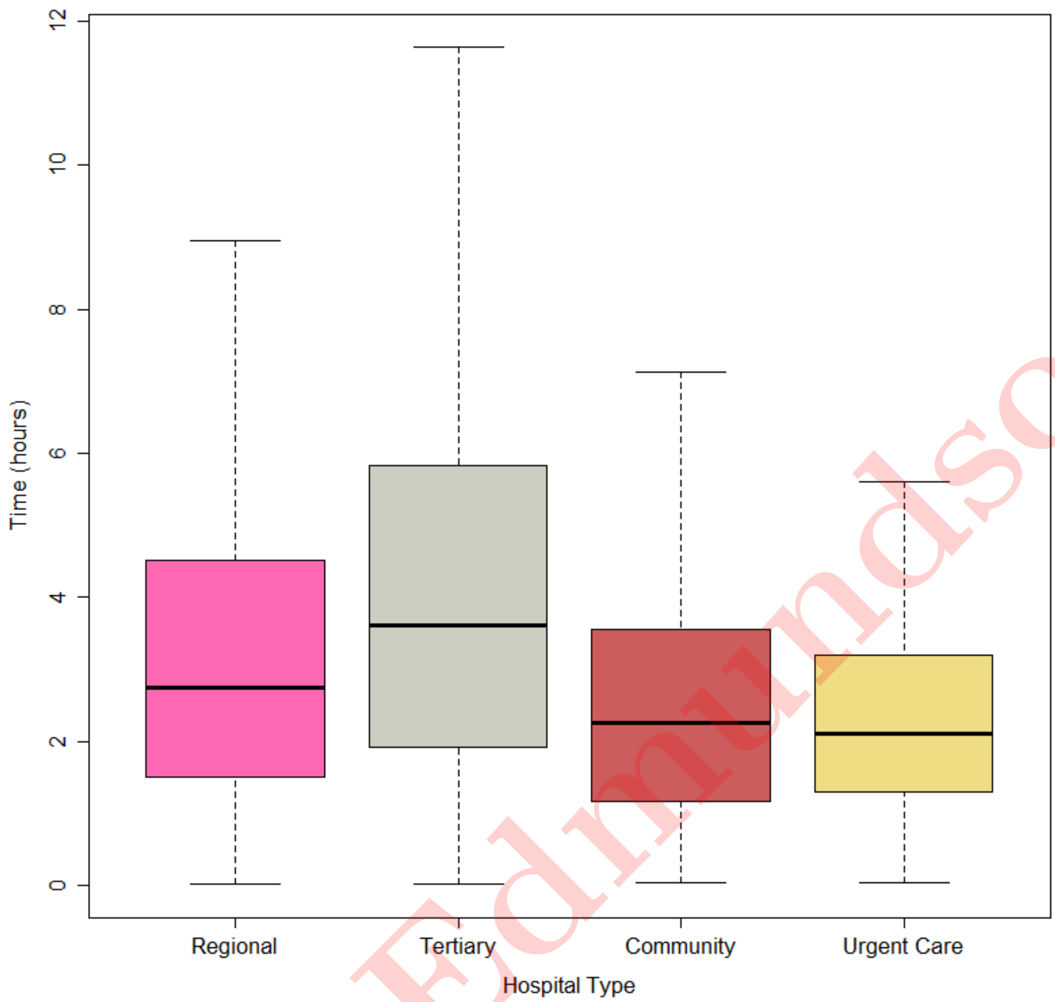

Figure 12: Box plots showing the time that patients spend in the ED before leaving against medical advice (LAMA). Times have been separated by ED type. Times over 24 hours were removed.

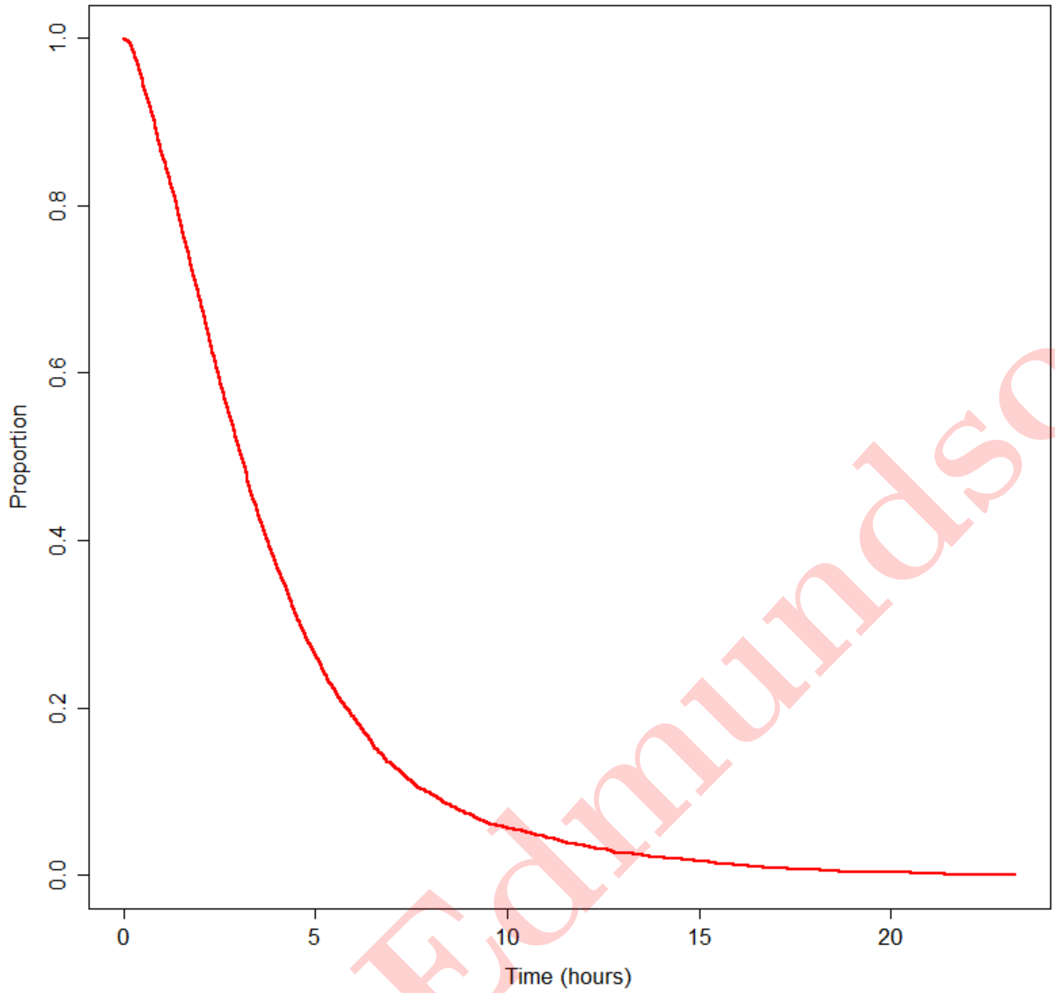

Figure 13: Kaplan-Meier curve showing the time that patients spend in the ED before leaving against medical advice (LAMA).

4.4 Trends in Presentation Times

Data were aggregated by time of day, day of week, and month of year to examine the timing of ED presentations. Overall, 5AM is the time of day in which the least number of people presented to any Albertan EDs with substance misuse related concerns (Figure 14, average of 4.57 presentations). These counts climb slowly throughout the day, peaking around 9PM (Figure 14, average of 11.32 presentations).

The number of presentations per day during the weekdays is comparatively stable, at around 198 per day, on average (Figure 15). These numbers peak on Saturday and Sunday at around 220 presentations per day (Figure 15).

Over the course of study period, the summer months were the most busy (Figure 16). The most presentations occurred in the month of July (6,599; 8.83%), and the least occurred during the month of February (5,194; 6.95%).

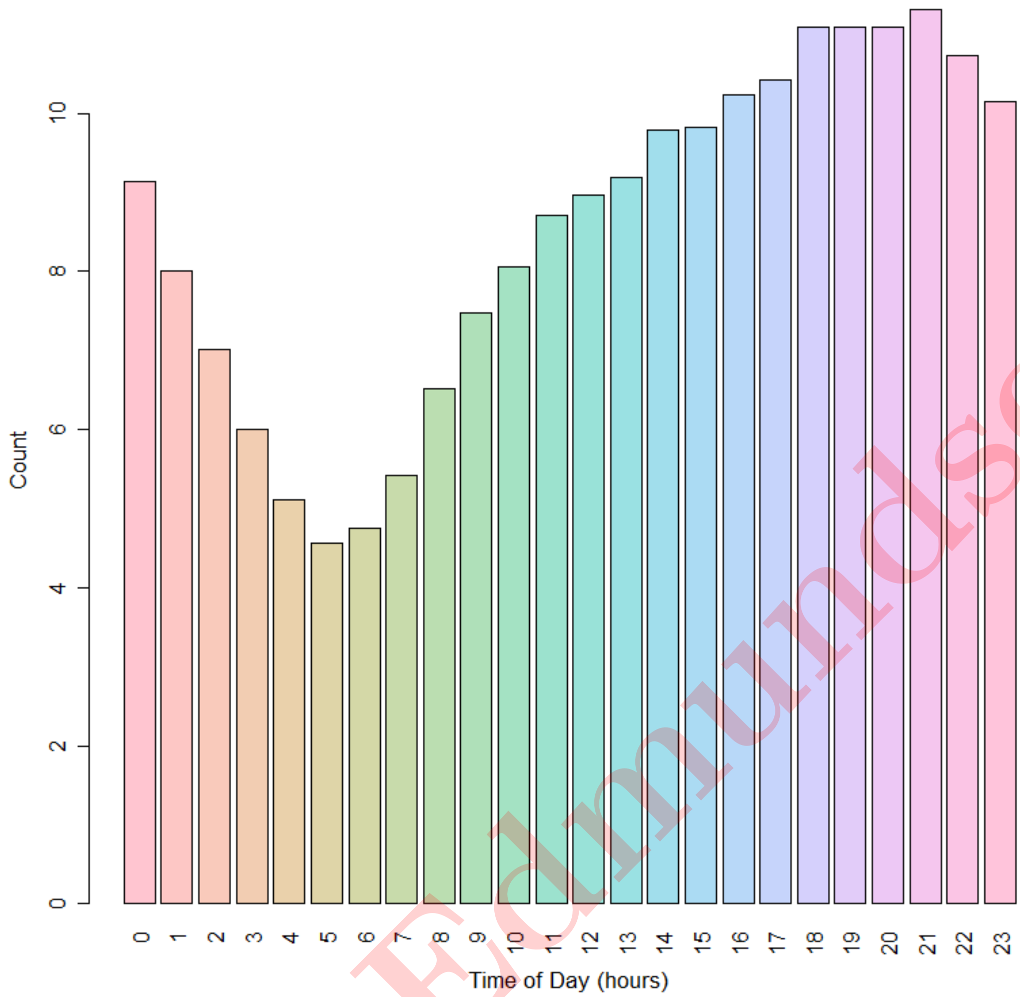

Figure 14: Bar plot showing the average number of presentations to all EDs in Alberta per hour. Hour 0 is midnight, hour 1 is 1AM, et cetera. (Colours do not mean anything, they are just pretty.)

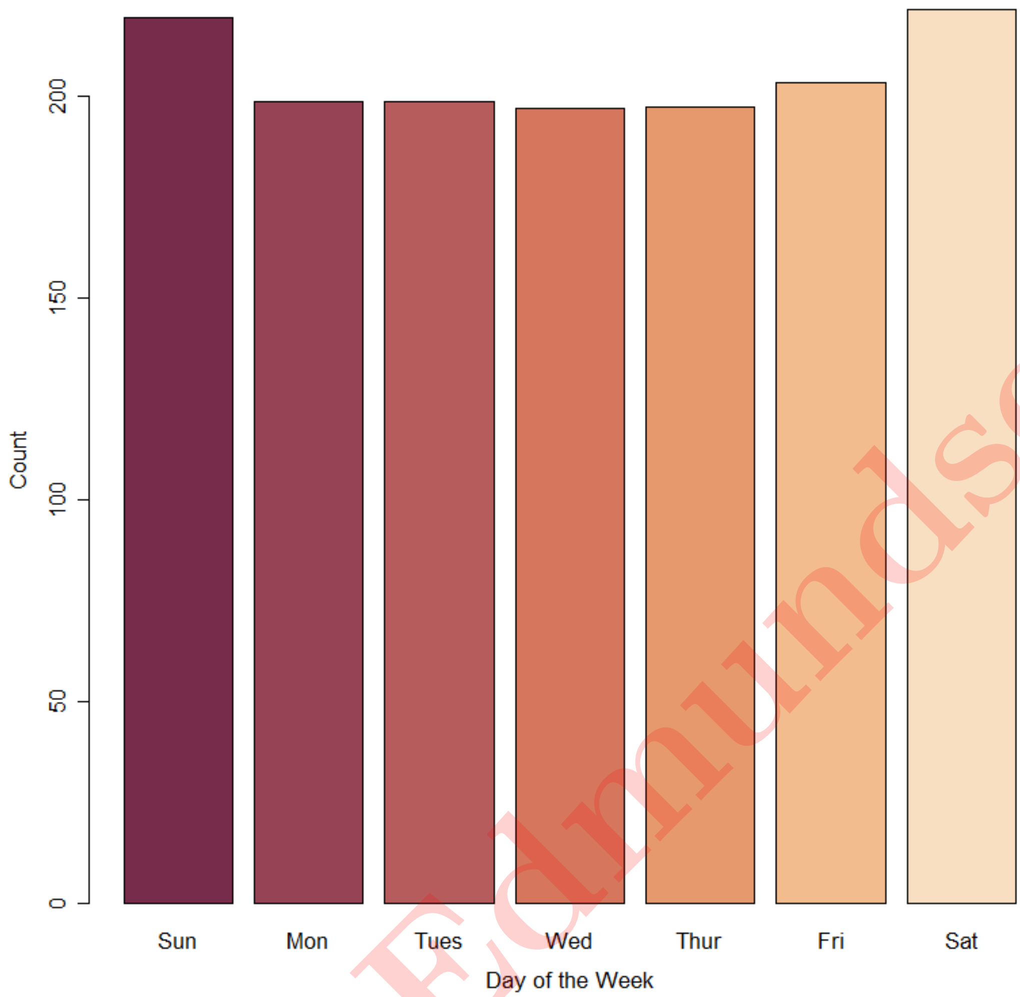

Figure 15: Bar plot showing the average number of presentations to all EDs in Alberta per day over the course of the week. (Colours do not mean anything, they are just pretty.)

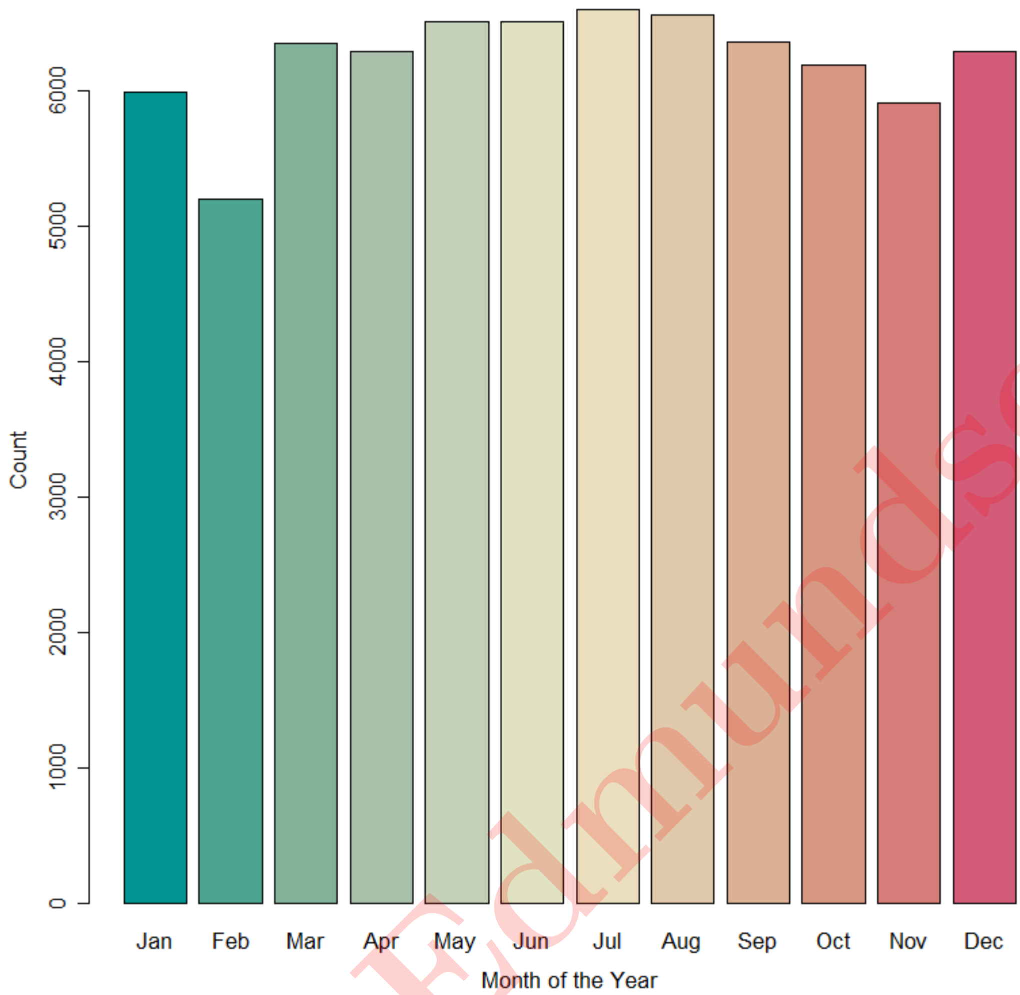

Figure 16: Bar plot showing the average number of presentations to all EDs in Alberta per month. (Colours do not mean anything, they are just pretty.)

4.5 Modelling & Hazard Ratios

Figure 17 shows the state structure of the present analysis. Upon presentation, individuals wait in the 'Start' state (state 1) until they are able to see the physician, whereupon they transition into the 'PIA' state (state 2). After this, the physician may decide to discharge the patient. Once this decision is made, the patient transitions to the 'discharge disposition decision' state (state 3). If the individual is to be admitted or transferred, they transition to the 'admit/transfer disposition decision' state once this decision is made by the physician (state 4). However, individuals may also choose to leave the ED after being seen. If the patient leaves before the physician reaches a disposition decision, they transition to the 'LAMA' state (state 7). If the physician decides to admit the patient, the patient transitions to the 'admission' state once they leave the ED and are admitted to the hospital (state 5). If the physician decides to transfer the patient, the patient transitions to the 'transfer' state once they leave the ED and are transferred to another institution (state 6).

The total number of transitions between each of the states is provided in Table 6. The counts in this table do not add up to the total sample size due to missing time data.

Table 7 shows the transition intensity matrix (as produced by `crudeinits.msm()`). These values indicate the overall instantaneous rates of transition between each state. The relative values in this table roughly correspond to the size of the counts in Table 6.

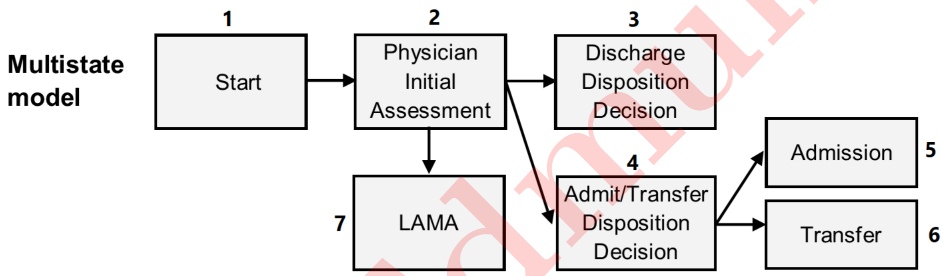

Figure 17: The state structure of the current multi-state model, illustrating patient flow throught the ED.

Table 6: The number of observed presentations for each allowed transition.

	State To						
State From	*1*	*2*	*3*	*4*	*5*	*6*	*7*
1 Start	0	61,165	0	0	0	0	0
2 PIA	0	0	43,189	15,763	0	0	1,417
3 Discharge Disp.	0	0	0	0	0	0	0
4 Adm./Tran. Disp.	0	0	0	0	12,906	4,204	0
5 Admitted	0	0	0	0	0	0	0
6 Transferred	0	0	0	0	0	0	0
7 LAMA	0	0	0	0	0	0	0

Table 7: Transition intensity matrix.

	State To						
State From	*1*	*2*	*3*	*4*	*5*	*6*	*7*
1 Start	-0.55	0.55	0	0	0	0	0
2 PIA	0	-0.17	0.12	0.04	0	0	0.004
3 Discharge Disp.	0	0	0	0	0	0	0
4 Adm./Tran. Disp.	0	0	0	-0.11	0.09	0.03	0
5 Admitted	0	0	0	0	0	0	0
6 Transferred	0	0	0	0	0	0	0
7 LAMA	0	0	0	0	0	0	0

4.5.1 Start to PIA (State 1 - 2)

Figure 18 and Table 8 show the estimates of the hazard ratios for the start to PIA transition (note that for many covariates, the 95% confidence intervals are small and are therefore masked by the symbol for the estimate). Hazard ratios that are greater than 1 signify that the time to transition is shorter for individuals of that group compared to the reference, and those that are less than 1 signify that the time to transition is longer for individuals of that group compared to the reference. Considering the univariate models, females are seen slightly faster than males, and younger people are seen slightly faster than older people. In addition, triage level 1 and rural remote municipality greatly increased the speed at which people were seen. After this point, the remainder of the written results refer only to the reduced model, not the univariate or full models.

Aside from gender, all the hypothesized covariates in the reduced model had a significant impact on transition times for 'start to PIA'. Similarly to the univariate models, CTAS level 1 (Resuscitation) had the largest effect. Indeed, those individuals triaged as CTAS level 1 saw the physician 3.75 times faster compared to those triaged as level 3. While not as substantive as triage level, patient municipality also had a significant effect on transition times. All of urban, rural and rural remote municipalities saw the physician quicker than patients from metropolitan municipalities. Another factor with a large effect on transition times was crowding level. Unsurprisingly, people presenting to a crowded ED wait longer to see a physician compared to those presenting to an uncrowded ED. (This makes sense, especially for this transition, considering that crowding level was defined as > or < 1 hour from arrival time to PIA.)

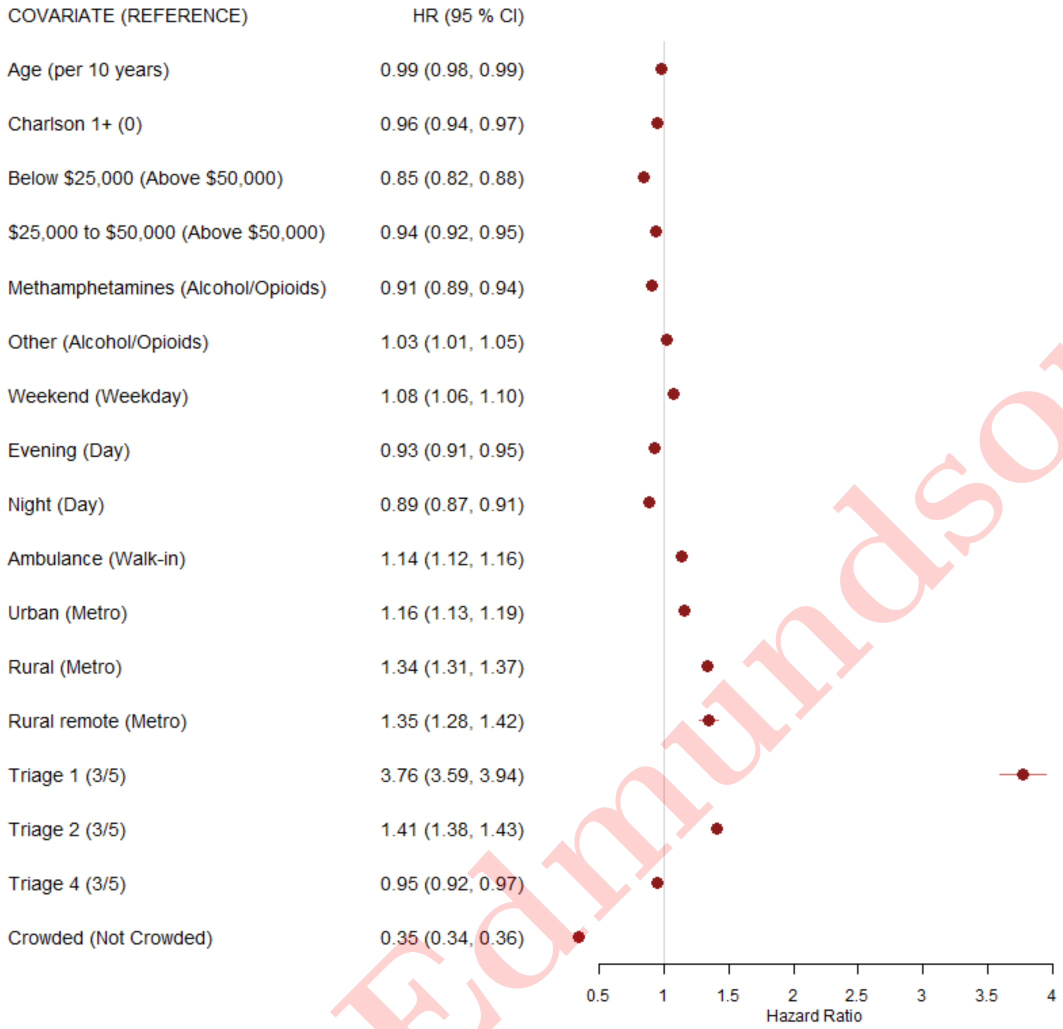

Figure 18: Forest plots summarizing the hazard ratios of each covariate group from the reduced model for the 'start to PIA' transition (State 1 - 2).

Table 8: Hazard ratios for all covariate groups from start to PIA (State 1 - 2).

Covariate	**Univariate Model** HR (95% CI)	**Full Model** HR (95% CI)	**Reduced Model** HR (95% CI)
Gender			
Male	Reference	Reference	
Female	1.06 (1.04, 1.07)*	0.98 (0.97, 1.00)	
Age *(Per 10 years)**	0.96 (0.95, 0.96)*	0.99 (0.98, 0.99)*	0.99 (0.98, 0.99)*
Charlson			
0	Reference	Reference	Reference
1+	0.87 (0.86, 0.89)*	0.96 (0.94, 0.97)*	0.96 (0.94, 0.97)*
Income			
Below $25,000	0.95 (0.92, 0.98)*	0.85 (0.82, 0.88)*	0.85 (0.82, 0.88)*
$25,000 - $50,000	0.94 (0.93, 0.96)*	0.94 (0.92, 0.95)*	0.94 (0.92, 0.95)*
Above $50,000	Reference	Reference	Reference
Diagnostic Code			
Alcohol	Reference	Reference	Reference
Amphetamines	0.86 (0.84, 0.88)*	0.92 (0.89, 0.94)*	0.91 (0.89, 0.94)*
Opioids	1.06 (1.03, 1.08)*	1.03 (1.00, 1.05)*	Combined with Reference
Other	1.14 (1.11, 1.16)*	1.04 (1.02, 1.06)*	1.03 (1.01, 1.05)*
Day of the Week			
Weekday	Reference	Reference	Reference
Weekend	1.11 (1.09, 1.13)*	1.08 (1.06, 1.10)*	1.08 (1.06, 1.10)*
Shift			
Day (0800 - 1559)	Reference	Reference	Reference
Evening (1600 - 2359)	0.89 (0.87, 0.90)*	0.93 (0.91, 0.95)*	0.93 (0.91, 0.95)*
Night (0000 - 0759)	0.89 (0.87, 0.91)*	0.89 (0.87, 0.91)*	0.89 (0.87, 0.91)*
Arrival by Ambulance			
Walk-in	Reference	Reference	Reference
Ambulance	1.17 (1.15, 1.19)*	1.14 (1.12, 1.16)*	1.14 (1.12, 1.16)*
Patient Municipality			
Metro	Reference	Reference	Reference
Urban	1.50 (1.46, 1.54)*	1.16 (1.13, 1.19)*	1.16 (1.13, 1.19)*
Rural	1.56 (1.53, 1.59)*	1.34 (1.31, 1.37)*	1.34 (1.31, 1.37)*
Rural Remote	1.58 (1.50, 1.67)*	1.35 (1.28, 1.43)*	1.35 (1.28, 1.42)*
Triage Level			
1	3.95 (3.78, 4.13)*	3.75 (3.58, 3.93)*	3.76 (3.59, 3.94)*
2	1.43 (1.40, 1.46)*	1.40 (1.38, 1.43)*	1.41 (1.38, 1.43)*
3	Reference	Reference	Reference
4	0.96 (0.93, 0.98)*	0.95 (0.92, 0.97)*	0.95 (0.92, 0.97)*
5	0.96 (0.90, 1.01)	0.97 (0.92, 1.04)	Combined with Reference
Crowding Level			
Not Crowded	Reference	Reference	Reference
Crowded	0.32 (0.31, 0.32)*	0.35 (0.34, 0.36)*	0.35 (0.34, 0.36)*

* indicates statistical significance.

4.5.2 PIA to Discharge Disposition Decision (State 2 - 3)

Figure 19 and Table 9 show the estimates of the hazard ratios for the PIA to discharge disposition decision transition. From PIA to discharge disposition decision, a patient's CTAS triage level had the largest impact on their transition time. Those individuals triaged as level 1 or 2 waited much longer to be discharged compared to those triaged at level 3, while those triaged as levels 4 or 5 were able to leave much sooner. The reason for presenting also had a large influence. Those individuals presenting with opioid-related concerns were discharged much faster than those presenting with alcohol or methamphetamine-related issues. Other notable factors that increased the time from PIA to discharge were mode of arrival, gender and comorbidity. Those patients arriving by ambulance waited longer to be discharged compared to patients who walked in. Females also waited longer, compared to males. Patients with one or more comorbid conditions also waited longer, when compared to those patients with no other significant health complications.

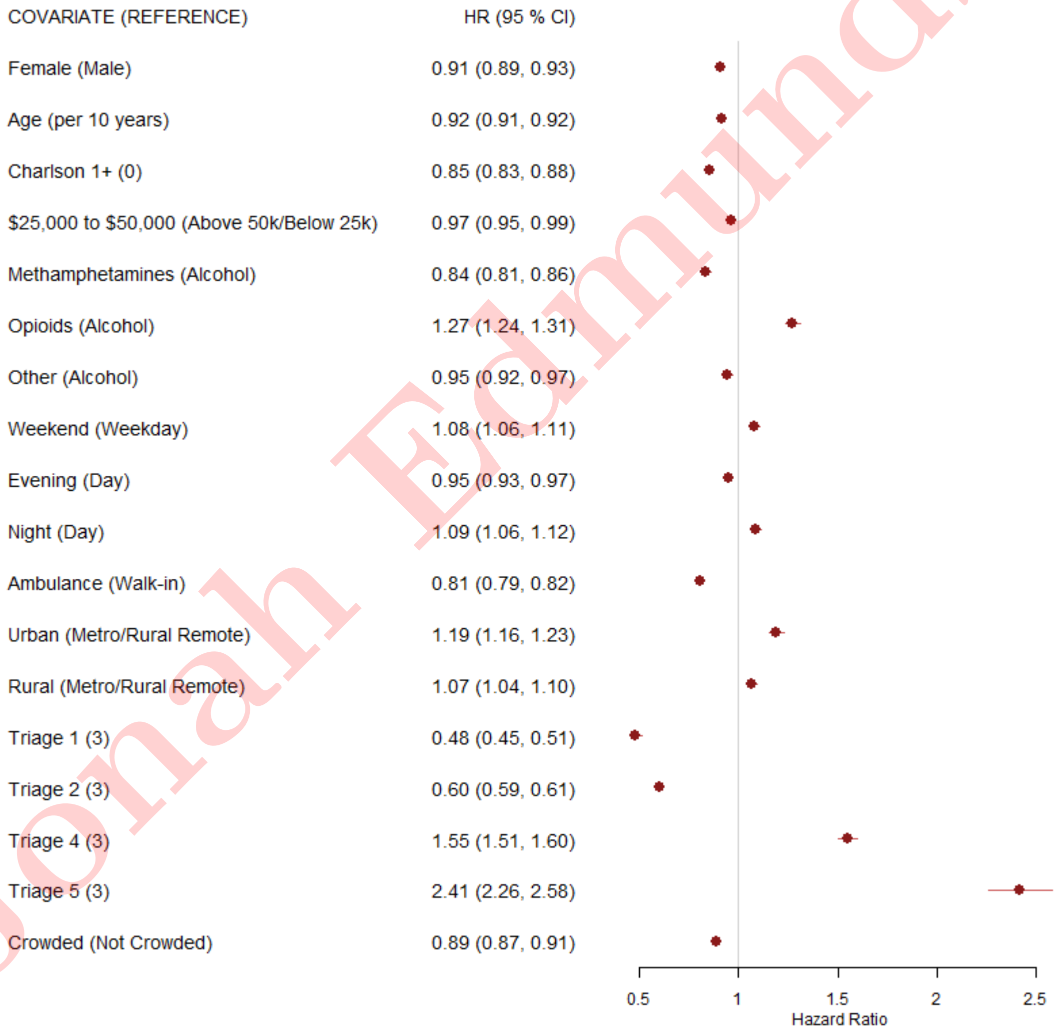

Figure 19: Forest plots summarizing the hazard ratios of each covariate group from the reduced model for the 'PIA to discharge disposition decision' transition (State 2 - 3).

Table 9: Hazard ratios for all covariate groups from PIA to discharge disposition decision (State 2 - 3).

Covariate	**Univariate Model** HR (95% CI)	**Full Model** HR (95% CI)	**Reduced Model** HR (95% CI)
Gender			
Male	Reference	Reference	Reference
Female	0.91 (0.90, 0.93)*	0.91 (0.89, 0.93)*	0.91 (0.89, 0.93)*
Age *(Per 10 years)**	0.92 (0.91, 0.93)*	0.92 (0.91, 0.92)*	0.92 (0.91, 0.92)*
Charlson			
0	Reference	Reference	Reference
1+	0.81 (0.79, 0.83)*	0.86 (0.83, 0.88)*	0.85 (0.83, 0.88)*
Income			
Below $25,000	1.07 (1.03, 1.11)*	0.97 (0.94, 1.01)	Combined with Reference
$25,000 - $50,000	0.98 (0.96, 1.00)*	0.96 (0.94, 0.98)*	0.97 (0.95, 0.99)*
Above $50,000	Reference	Reference	Reference
Diagnostic Code			
Alcohol	Reference	Reference	Reference
Amphetamines	0.91 (0.88, 0.94)*	0.84 (0.81, 0.86)*	0.84 (0.81, 0.86)*
Opioids	1.22 (1.19, 1.26)*	1.27 (1.24, 1.31)*	1.27 (1.24, 1.31)*
Other	0.94 (0.92, 0.96)*	0.95 (0.92, 0.97)*	0.95 (0.92, 0.97)*
Day of the Week			
Weekday	Reference	Reference	Reference
Weekend	1.10 (1.07, 1.12)*	1.08 (1.06, 1.11)*	1.08 (1.06, 1.11)*
Shift			
Day (0800 - 1559)	Reference	Reference	Reference
Evening (1600 - 2359)	0.92 (0.90, 0.94)*	0.95 (0.93, 0.97)*	0.95 (0.93, 0.97)*
Night (0000 - 0759)	1.14 (1.11, 1.16)*	1.09 (1.06, 1.12)*	1.09 (1.06, 1.12)*
Arrival by Ambulance			
Walk-in	Reference	Reference	Reference
Ambulance	0.72 (0.71, 0.74)*	0.81 (0.79, 0.82)*	0.81 (0.79, 0.82)*
Patient Municipality			
Metro	Reference	Reference	Reference
Urban	1.40 (1.36, 1.44)*	1.19 (1.15, 1.23)*	1.19 (1.16, 1.23)*
Rural	1.25 (1.22, 1.28)*	1.07 (1.04, 1.11)*	1.07 (1.04, 1.10)*
Rural Remote	1.31 (1.23, 1.40)*	1.00 (0.94, 1.07)	Combined with Reference
Triage Level			
1	0.48 (0.45, 0.51)*	0.48 (0.45, 0.51)*	0.48 (0.45, 0.51)*
2	0.61 (0.60, 0.63)*	0.60 (0.59, 0.61)*	0.60 (0.59, 0.61)*
3	Reference	Reference	Reference
4	1.58 (1.53, 1.62)*	1.55 (1.51, 1.60)*	1.55 (1.51, 1.60)*
5	2.63 (2.47, 2.80)*	2.42 (2.26, 2.59)*	2.42 (2.26, 2.58)*
Crowding Level			
Not Crowded	Reference	Reference	Reference
Crowded	0.78 (0.76, 0.79)*	0.90 (0.87, 0.91)*	0.89 (0.87, 0.91)*

* indicates statistical significance.

4.5.3 PIA to Admit/Transfer Disposition Decision (State 2 - 4)

Figure 20 and Table 10 show the estimates of the hazard ratios for the PIA to admit & transfer disposition decision transition. Considering the time from PIA to decision to admit or transfer the patient, patient municipality was the most substantive factor. Physicians caring for patients from all of urban, rural, and rural remote municipalities were able to make the admission/transfer decision faster than physicians seeing patients from metropolitan municipalities. Triage code 1 also had a significant impact, with patients triaged at this level being admitted/transferred much faster than patients receiving less urgent codes. Time of day is also important, as physicians caring for patients at night (0000 - 0759) or during the evening (1600 - 2359) were much slower to make the admit/transfer decision than those physicians seeing patients during the day. Additionally, patients presenting from lower income neighbourhoods (< \$25,000 per year) waited longer for this disposition decision.

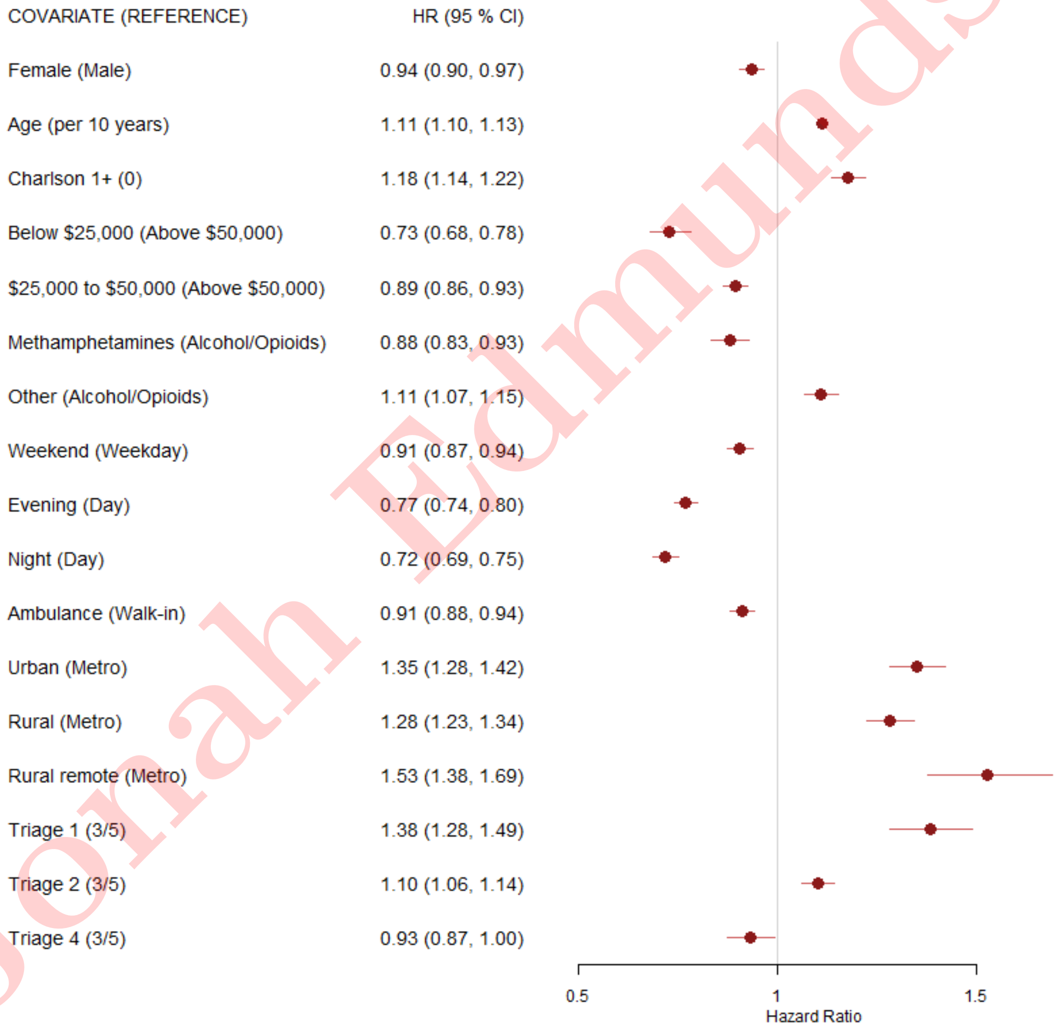

Figure 20: Forest plots summarizing the hazard ratios of each covariate group from the reduced model for the 'PIA to disposition decision' transition (State 2 - 4).

Table 10: Hazard ratios for all covariate groups from PIA to admit/transfer disposition decision (State 2 - 4).

Covariate	**Univariate Model** HR (95% CI)	**Full Model** HR (95% CI)	**Reduced Model** HR (95% CI)
Gender			
Male	Reference	Reference	Reference
Female	0.92 (0.89, 0.95)*	0.94 (0.90, 0.97)*	0.94 (0.90, 0.97)*
Age *(Per 10 years)**	1.13 (1.11, 1.14)*	1.11 (1.10, 1.13)*	1.11 (1.10, 1.13)*
Charlson			
0	Reference	Reference	Reference
1+	1.28 (1.24, 1.32)*	1.18 (1.14, 1.22)*	1.18 (1.14, 1.22)*
Income			
Below $25,000	0.83 (0.78, 0.88)*	0.73 (0.68, 0.78)*	0.73 (0.68, 0.78)*
$25,000 - $50,000	0.91 (0.88, 0.95)*	0.89 (0.87, 0.93)*	0.89 (0.87, 0.93)*
Above $50,000	Reference	Reference	Reference
Diagnostic Code			
Alcohol	Reference	Reference	Reference
Amphetamines	0.75 (0.71, 0.79)*	0.88 (0.83, 0.93)*	0.88 (0.83, 0.93)*
Opioids	0.96 (0.92, 1.01)	1.00 (0.95, 1.06)	Combined with Reference
Other	1.02 (0.99, 1.06)	1.11 (1.07, 1.16)*	1.11 (1.07, 1.16)*
Day of the Week			
Weekday	Reference	Reference	Reference
Weekend	0.88 (0.85, 0.92)*	0.91 (0.87, 0.94)*	0.91 (0.87, 0.94)*
Shift			
Day (0800 - 1559)	Reference	Reference	Reference
Evening (1600 - 2359)	0.76 (0.74, 0.79)*	0.77 (0.74, 0.80)*	0.77 (0.74, 0.80)*
Night (0000 - 0759)	0.68 (0.65, 0.71)*	0.72 (0.69, 0.75)*	0.72 (0.69, 0.75)*
Arrival by Ambulance			
Walk-in	Reference	Reference	Reference
Ambulance	0.96 (0.93, 0.99)*	0.91 (0.88, 0.94)*	0.91 (0.88, 0.94)*
Patient Municipality			
Metro	Reference	Reference	Reference
Urban	1.31 (1.25, 1.38)*	1.36 (1.29, 1.43)*	1.35 (1.28, 1.42)*
Rural	1.18 (1.13, 1.23)*	1.29 (1.23, 1.35)*	1.28 (1.23, 1.34)*
Rural Remote	1.38 (1.25, 1.53)*	1.53 (1.38, 1.70)*	1.53 (1.38, 1.69)*
Triage Level			
1	1.23 (1.15, 1.32)*	1.39 (1.29, 1.49)*	1.38 (1.29, 1.49)*
2	1.03 (0.99, 1.06)	1.10 (1.07, 1.15)*	1.10 (1.06, 1.14)*
3	Reference	Reference	Reference
4	0.95 (0.89, 1.01)	0.94 (0.88, 1.00)*	0.93 (0.87, 1.00)*
5	1.12 (0.94, 1.33)	1.14 (0.95, 1.37)	Combined with Reference
Crowding Level			
Not Crowded	Reference	Reference	
Crowded	0.93 (0.89, 0.96)*	1.01 (0.97, 1.05)	

* indicates statistical significance.

4.5.4 Disposition to Admission (State 4 - 5)

Figure 21 and Table 11 show the estimates of the hazard ratios for the disposition decision to admission transition. Once the physician made the decision to admit the patient, patient municipality was the most influential factor in deciding the wait time from disposition to admission. Patients presenting from urban and rural municipalities were admitted faster than individuals from metropolitan municipalities, and those from rural remote municipalities were admitted *much* faster. On the other hand, those patients presenting with methamphetamine-related concerns were much slower to be admitted compared to those presenting with alcohol-related concerns. Crowding also influenced this transition, with patients presenting to a crowded ED waiting longer than those presenting to a non-crowded ED.

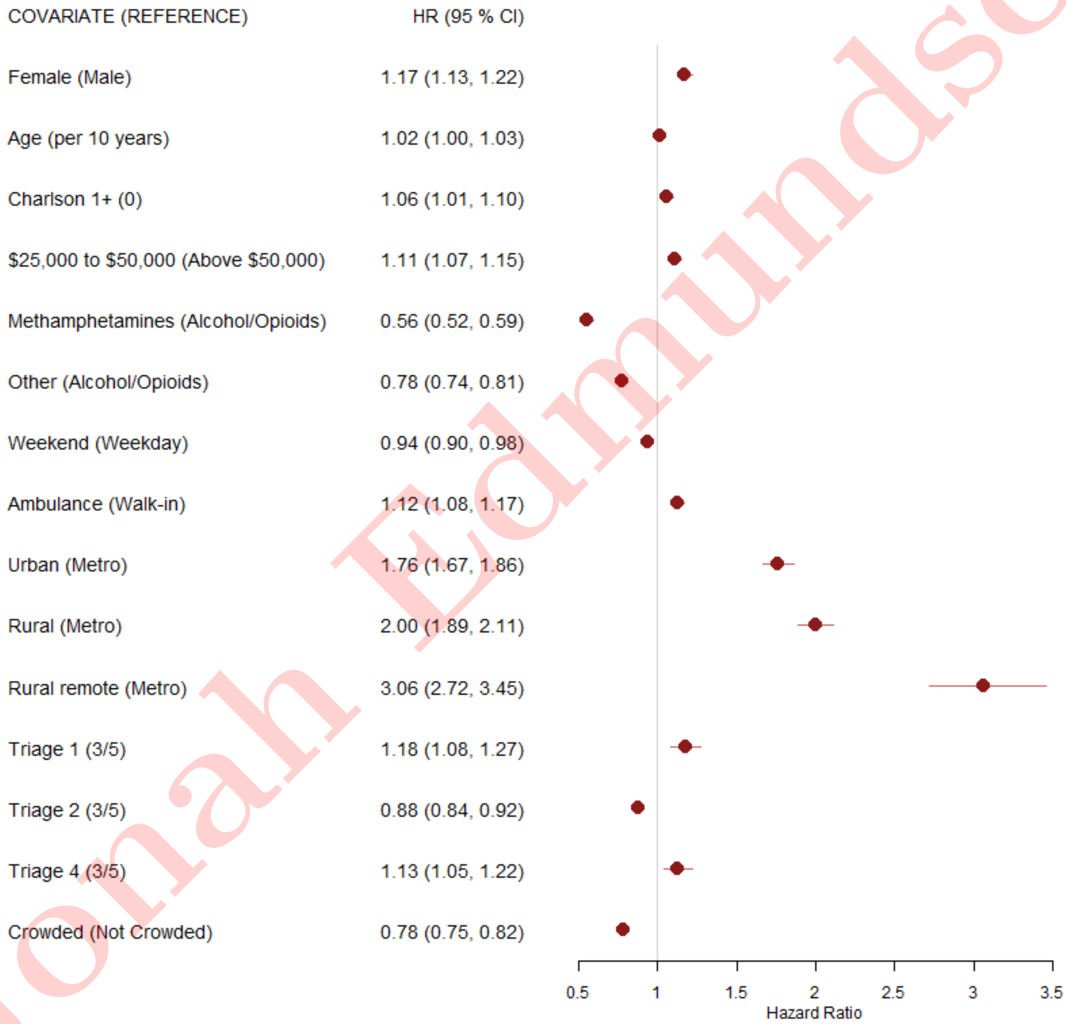

Figure 21: Forest plots summarizing the hazard ratios of each covariate group from the reduced model for the 'disposition to admission' transition (State 4 - 5).

Table 11: Hazard ratios for all covariate groups from disposition decision to admission (State 4 - 5).

Covariate	**Univariate Model** HR (95% CI)	**Full Model** HR (95% CI)	**Reduced Model** HR (95% CI)
Gender			
Male	Reference	Reference	Reference
Female	1.14 (1.10, 1.18)*	1.18 (1.13, 1.22)*	1.17 (1.13, 1.22)*
Age *(Per 10 years)**	1.07 (1.06, 1.08)*	1.02 (1.00, 1.03)*	1.02 (1.00, 1.03)*
Charlson			
0	Reference	Reference	Reference
1+	1.25 (1.21, 1.30)*	1.06 (1.01, 1.10)*	1.06 (1.01, 1.10)*
Income			
Below $25,000	1.41 (1.31, 1.51)*	0.78 (0.71, 0.85)*	0.78 (0.71, 0.85)*
$25,000 - $50,000	1.17 (1.13, 1.22)*	1.11 (1.07, 1.15)*	1.11 (1.07, 1.15)*
Above $50,000	Reference	Reference	Reference
Diagnostic Code			
Alcohol	Reference	Reference	Reference
Amphetamines	0.48 (0.45, 0.51)*	0.55 (0.52, 0.59)*	0.56 (0.52, 0.59)*
Opioids	0.98 (0.93, 1.04)	0.98 (0.92, 1.05)	Combined with Reference
Other	0.70 (0.67, 0.73)*	0.78 (0.74, 0.81)*	0.78 (0.74, 0.81)*
Day of the Week			
Weekday	Reference	Reference	Reference
Weekend	0.96 (0.92, 0.99)*	0.94 (0.90, 0.98)*	0.94 (0.90, 0.98)*
Shift			
Day (0800 - 1559)	Reference	Reference	
Evening (1600 - 2359)	0.97 (0.93, 1.01)	0.99 (0.95, 1.03)	
Night (0000 - 0759)	1.08 (1.03, 1.13)*	1.05 (1.00, 1.10)	
Arrival by Ambulance			
Walk-in	Reference	Reference	Reference
Ambulance	1.23 (1.19, 1.27)*	1.12 (1.08, 1.17)*	1.12 (1.08, 1.17)*
Patient Municipality			
Metro	Reference	Reference	Reference
Urban	1.98 (1.88, 2.09)*	1.77 (1.67, 1.87)*	1.76 (1.67, 1.86)*
Rural	2.40 (2.30, 2.51)*	2.00 (1.89, 2.11)*	2.00 (1.89, 2.11)*
Rural Remote	5.28 (4.83, 5.79)*	3.08 (2.74, 3.48)*	3.06 (2.72, 3.45)*
Triage Level			
1	1.05 (0.97, 1.13)	1.17 (1.08, 1.27)*	1.18 (1.08, 1.27)*
2	0.77 (0.74, 0.80)*	0.88 (0.84, 0.92)*	0.88 (0.84, 0.92)*
3	Reference	Reference	Reference
4	1.10 (1.03, 1.19)*	1.13 (1.05, 1.23)*	1.13 (1.05, 1.22)*
5	1.00 (0.80, 1.24)	0.90 (0.71, 1.15)	Combined with Reference
Crowding Level			
Not Crowded	Reference	Reference	Reference
Crowded	0.62 (0.60, 0.65)*	0.79 (0.76, 0.83)*	0.78 (0.75, 0.82)*

* indicates statistical significance.

4.5.5 Disposition to Transfer (State 4 - 6)

Figure 22 and Table 12 show the estimates of the hazard ratios for the disposition decision to transfer transition. Once the decision had been made to transfer the patient, patient municipality was the most substantive factor for influencing the time to transfer. While patients from rural and rural remote areas were transferred quicker than patients from metropolitan zones, patients from urban centres were transferred much slower than patients from metropolitan zones. Triage level was also important. Interestingly, patients triaged as less urgent (levels 4 & 5) were transferred quicker than patients triaged as more urgent (levels 1, 2 & 3). Additionally, those patients presenting with opioids-related concerns were transferred faster than those with alcohol-related issues.

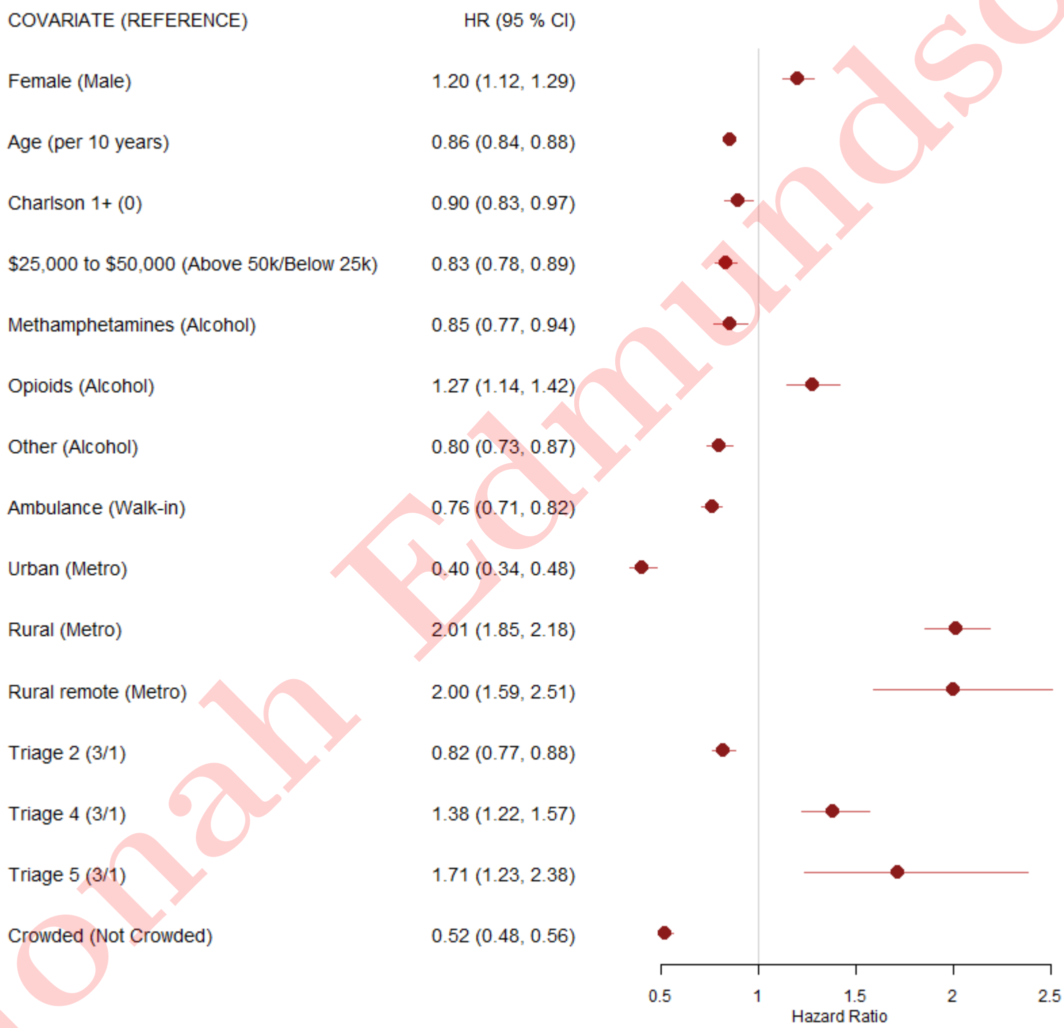

Figure 22: Forest plots summarizing the hazard ratios of each covariate group from the reduced model for the 'disposition to transfer' transition (State 4 - 6).

Table 12: Hazard ratios for all covariate groups from disposition decision to transfer (State 4 - 6).

Covariate	**Univariate Model** HR (95% CI)	**Full Model** HR (95% CI)	**Reduced Model** HR (95% CI)
Gender			
Male	Reference	Reference	Reference
Female	1.19 (1.12, 1.27)*	1.20 (1.12, 1.29)*	1.20 (1.12, 1.29)*
Age *(Per 10 years)**	0.85 (0.83, 0.87)*	0.86 (0.83, 0.88)*	0.86 (0.84, 0.88)*
Charlson			
0	Reference	Reference	Reference
1+	0.82 (0.76, 0.88)*	0.90 (0.83, 0.97)*	0.90 (0.83, 0.97)*
Income			
Below $25,000	1.67 (1.50, 1.87)*	0.98 (0.86, 1.12)	Combined with Reference
$25,000 - $50,000	0.87 (0.81, 0.93)*	0.83 (0.77, 0.89)*	0.83 (0.78, 0.89)*
Above $50,000	Reference	Reference	Reference
Diagnostic Code			
Alcohol	Reference	Reference	Reference
Amphetamines	1.03 (0.94, 1.13)	0.85 (0.77, 0.94)*	0.85 (0.77, 0.94)*
Opioids	1.33 (1.21, 1.47)*	1.27 (1.14, 1.42)*	1.28 (1.15, 1.42)*
Other	0.96 (0.89, 1.03)	0.80 (0.73, 0.87)*	0.80 (0.73, 0.87)*
Day of the Week			
Weekday	Reference	Reference	
Weekend	1.03 (0.96, 1.10)	0.99 (0.92, 1.06)	
Shift			
Day (0800 - 1559)	Reference	Reference	Reference
Evening (1600 - 2359)	1.14 (1.06, 1.22)*	1.11 (1.03, 1.19)*	1.11 (1.03, 1.19)*
Night (0000 - 0759)	1.22 (1.13, 1.33)*	1.10 (1.00, 1.20)*	1.10 (1.00, 1.20)*
Arrival by Ambulance			
Walk-in	Reference	Reference	Reference
Ambulance	0.79 (0.74, 0.84)*	0.76 (0.71, 0.82)*	0.76 (0.71, 0.82)*
Patient Municipality			
Metro	Reference	Reference	Reference
Urban	0.53 (0.45, 0.62)*	0.40 (0.34, 0.48)*	0.40 (0.34, 0.48)*
Rural	2.70 (2.51, 2.90)*	2.02 (1.84, 2.21)*	2.01 (1.85, 2.18)*
Rural Remote	3.64 (3.03, 4.37)*	2.00 (1.59, 2.51)*	2.00 (1.59, 2.51)*
Triage Level			
1	1.09 (0.95, 1.25)	0.99 (0.85, 1.15)	Combined with Reference
2	0.83 (0.77, 0.88)*	0.82 (0.76, 0.88)*	0.82 (0.77, 0.88)*
3	Reference	Reference	Reference
4	1.42 (1.27, 1.60)*	1.38 (1.22, 1.57)*	1.39 (1.22, 1.57)*
5	1.66 (1.21, 2.26)*	1.72 (1.23, 2.39)*	1.72 (1.23, 2.38)*
Crowding Level			
Not Crowded	Reference	Reference	Reference
Crowded	0.49 (0.46, 0.53)*	0.52 (0.48, 0.56)*	0.52 (0.48, 0.56)*

* indicates statistical significance.

4.5.6 PIA to LAMA (State 2 - 7)

Figure 23 and Table 13 show the estimates of the hazard ratios for the PIA to LAMA transition. Several covariates had strong associations with patient tendency to leave against medical advice. Those patients who LAMA did so much faster if they had less urgent triage codes (levels 4 & 5 compared to 1, 2 & 3). Income was also a substantive factor, as LAMA patients from low income neighbourhoods left much faster than those from higher income neighbourhoods. Interestingly, patients presenting with opioids related issues who LAMA did so much faster than those receiving other diagnostic codes. Lastly, patient municipality was, again, very influential. Those patients who LAMA from all of urban, rural, and rural remote municipalities waited much longer until leaving (ie. were more patient) than those individuals from metropolitan areas.

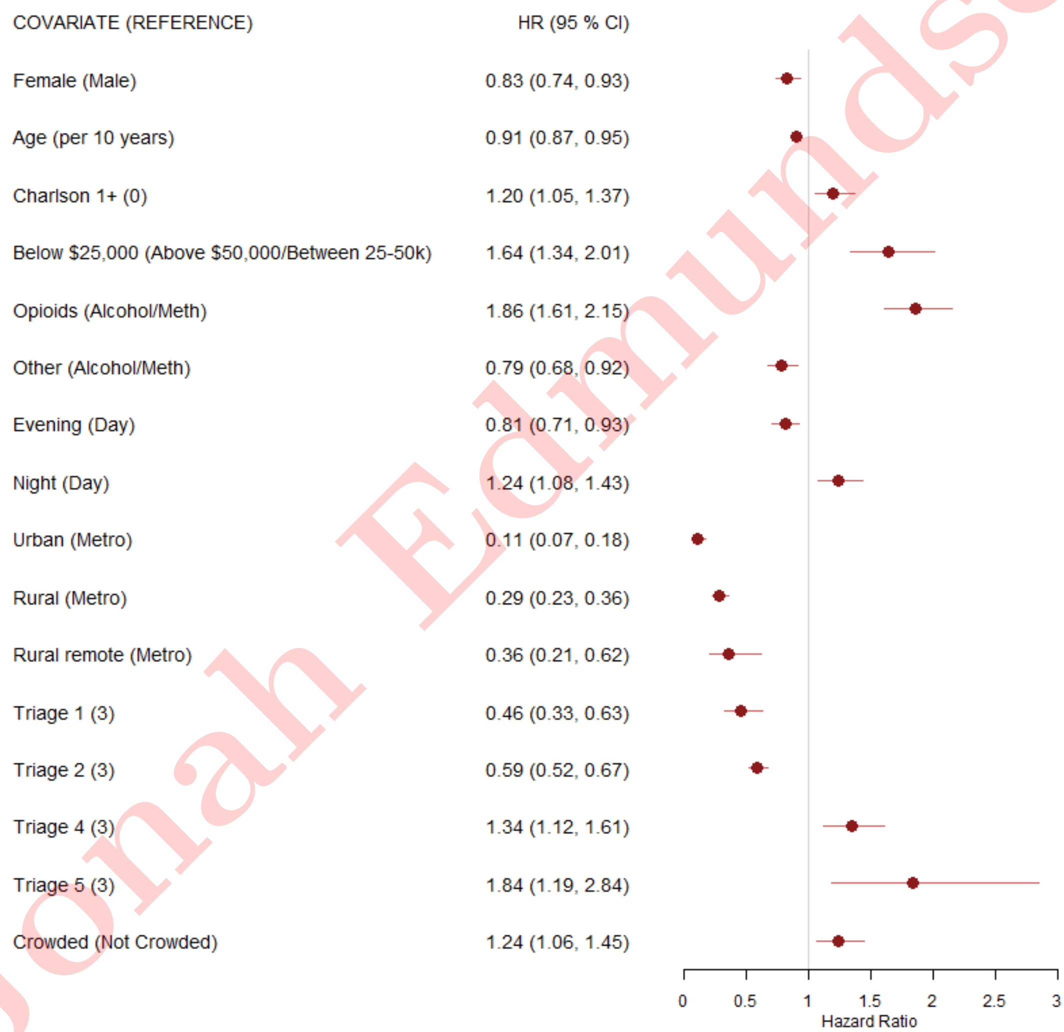

Figure 23: Forest plots summarizing the hazard ratios of each covariate group from the reduced model for the 'PIA to LAMA' transition (State 2 - 7).

Table 13: Hazard ratios for all covariate groups from PIA to LAMA (State 2 - 7).

Covariate	**Univariate Model** HR (95% CI)	**Full Model** HR (95% CI)	**Reduced Model** HR (95% CI)
Gender			
Male	Reference	Reference	Reference
Female	0.81 (0.73, 0.90)*	0.83 (0.74, 0.93)*	0.83 (0.74, 0.93)*
Age *(Per 10 years)**	0.97 (0.93, 1.00)	0.91 (0.88, 0.96)*	0.91 (0.87, 0.95)*
Charlson			
0	Reference	Reference	Reference
1+	1.29 (1.16, 1.44)*	1.21 (1.06, 1.37)*	1.20 (1.05, 1.37)*
Income			
Below $25,000	1.18 (0.97, 1.44)	1.69 (1.37, 2.09)*	1.64 (1.34, 2.01)*
$25,000 - $50,000	1.02 (0.91, 1.15)	1.07 (0.95, 1.21)	Combined with Reference
Above $50,000	Reference	Reference	Reference
Diagnostic Code			
Alcohol	Reference	Reference	Reference
Amphetamines	1.29 (1.11, 1.50)*	1.18 (1.00, 1.40)	Combined with Reference
Opioids	1.95 (1.70, 2.24)*	1.94 (1.67, 2.26)*	1.86 (1.61, 2.15)*
Other	0.75 (0.65, 0.87)*	0.83 (0.70, 0.97)*	0.79 (0.68, 0.92)*
Day of the Week			
Weekday	Reference	Reference	
Weekend	1.11 (0.99, 1.24)	1.12 (0.99, 1.26)	
Shift			
Day (0800 - 1559)	Reference	Reference	Reference
Evening (1600 - 2359)	0.79 (0.70, 0.90)*	0.82 (0.71, 0.94)*	0.81 (0.71, 0.93)*
Night (0000 - 0759)	1.28 (1.12, 1.46)*	1.25 (1.08, 1.44)*	1.24 (1.08, 1.43)*
Arrival by Ambulance			
Walk-in	Reference	Reference	
Ambulance	0.90 (0.81, 1.00)*	0.97 (0.86, 1.09)	
Patient Municipality			
Metro	Reference	Reference	Reference
Urban	0.11 (0.07, 0.18)*	0.11 (0.07, 0.18)*	0.11 (0.07, 0.18)*
Rural	0.34 (0.27, 0.42)*	0.29 (0.23, 0.37)*	0.29 (0.23, 0.36)*
Rural Remote	0.41 (0.24, 0.70)*	0.36 (0.21, 0.63)*	0.36 (0.21, 0.62)*
Triage Level			
1	0.51 (0.37, 0.69)*	0.46 (0.33, 0.63)*	0.46 (0.33, 0.63)*
2	0.60 (0.54, 0.68)*	0.59 (0.52, 0.67)*	0.59 (0.52, 0.67)*
3	Reference	Reference	Reference
4	1.41 (1.20, 1.65)*	1.33 (1.11, 1.60)*	1.34 (1.12, 1.61)*
5	1.80 (1.19, 2.73)*	1.78 (1.15, 2.77)*	1.84 (1.19, 2.84)*
Crowding Level			
Not Crowded	Reference	Reference	Reference
Crowded	1.68 (1.46, 1.94)*	1.24 (1.06, 1.44)*	1.24 (1.06, 1.45)*

* indicates statistical significance.

4.6 Model Evaluation

The full model (all covariates for all transitions) was reduced to a model including only significant covariates, as described in the Methods section above. To do this, five nested models were created. As determined by comparing log-likelihood values and a likelihood-ratio test, the reduced model provides the best fit to the given data (Table 14). AIC was also used to determine which model was the most parsimonious (a lower AIC value indicates increased parsimony). AIC values indicate that the reduced model is the most parsimonious.

Table 14: Model evaluation parameters.

Model #	**df**	**Log-Likelihood**	**LR test (p-value)**	**AIC**
Full Model	126	-324,489	0.11	649,229
Mod2	120	-324,492	0.10	649,224
Mod3	114	-324,497	0.14	649,221
Mod4	109	-324,501	0.33	649,219
Reduced Model	107	-324,502	Reference	649,218

5 Discussion

The present analysis has investigated the effects of various covariates on the flow of patients who present substance misuse through Alberta EDs. To complete this analysis, data was extracted from the NACRS dataset for all Albertans between April 1, 2019, to March 31, 2020. The data analyzed had 74,455 presentations from 40,995 patients. I deconstructed the flow of a patient through the ED into seven mutually-exclusive states: 'start', 'PIA', 'discharge disposition decision', 'admit/transfer disposition decision', 'admitted', 'transferred', and 'LAMA'. I considered covariates on patient characteristics and ED visit characteristics that may influence the transition times between states. Models were initially fit to each covariate separately. Then, a model with all covariates were removed to achieve a reduced model with key covariates. While previous studies have used a similar approach to modelling ED flow data, the present analysis is set apart by its focus on patients presenting with substance misuse.

While most covariates had a statistically significant effect on all state transitions, each transition showed different key variables that exerted the strongest influence. Multi-state modelling revealed that, for the start to PIA transition, triage level 1 (resuscitation) had the most substantive effect on decreasing the time required for an individual to be seen when compared to triage level 3, while ED crowding had the strongest opposite effect. For the subsequent transition (PIA to discharge disposition decision), triage level 1 had the reverse effect, being the most influential covariate in increasing time to transition (compared again to triage level 3). Conversely, the least urgent triage code, level 5, had the greatest influence on decreasing time to transition. These results are unsurprising, given that the primary purpose of triage is to allow ED workers to sort patients into those who should be seen sooner versus those who can wait. When considering the PIA to admit/transfer disposition decision, night time was the most substantive covariate for slowing transition times (compared to those patients arriving during the day). One possible explanation for this could be short staffing during the night shift. Also exerting a strong effect on times for this transition is patient municipality. Patients presenting from all of urban, rural and rural remote municipalities moved much faster through this transition when compared to patients presenting from metropolitan municipalities. Similar results were also found for the transitions to admission and transfer from disposition decision. When it came to patients that LAMA, patient municipality was the most important factor in increasing time to transition. In this case, patients from non-metropolitan areas waited much longer to leave. This could be due to increased patience on behalf of these individuals, or perhaps due to a lack of access to alternate health care services.

A unique contribution of the present study to the literature is the inclusion of substance type in the multi-state model. The factor levels used for this variable include 'alcohol' (reference), 'methamphetamines', 'opioids' and 'other'. Of these, the 'opioids' category was non-significant on half of the analyzed state transitions. On the 'PIA to Discharge disp.', 'Disp. to Transferred' and 'PIA to LAMA' transitions, however, it decreased time to transition (compared to those presenting with alcohol-related concerns). In contrast, patients presenting with methamphetamine-related concerns consistently had longer times to transition, except for the 'PIA to LAMA' transition, where it was non-significant. The 'other' category did not have a consistent effect on transition times when compared to 'alcohol'.

Across all transitions, the triage level and patient municipality covariates has the largest effect on transition times. While the findings related to triage level are reassuring and perhaps unsurprising, the results related to the effect of patient municipality on transition times is possibly the most major finding. Assuming that patients most often present to EDs in their own municipality, the large magnitude of the effect of patient municipality on ED flow suggests that EDs in non-metropolitan areas operate differently than metropolitan EDs. This difference could be due to a multitude of causes, including but not limited to: relatively less patient presentations per ED physician in rural areas compared to metropolitan areas, different administrative systems for processing patients, or relatively more infrastructure per total number of patient presentations in rural areas compared to metropolitan areas.

Many of the results of the present study are similar to those results already in the literature for other patient populations. In regards to ED crowding, both Peltan et al. (2018) and Kroetch et al. (2021) found that ED crowding was associated with ED wait times. In the study from Peltan et al. (2018), ED crowding (defined as having more registered patients than ED beds) was associated with longer overall lengths of stay. In the study from Kroetch et al. (2021), ED crowding (defined as start to PIA $>$ 1 hour) was associated with longer wait times from start to PIA and disposition to departure.

Liu et al. (2019) found that while age and gender were both significant for all investigated transitions, their actual effect was quite small. This is comparable to the present results, except gender was found not to be significant for the start to PIA transition. They also found that higher acuity levels decreased the start to PIA time. This matches the findings of the current study. While Liu et al. (2019) also investigated time of day, their grouping was different than the current study, making the results difficult to compare. In a recently published article by Rizk et al. (2021), authors found that patients presenting at night transitioned more quickly from PIA to discharge, but spent more time waiting from triage to PIA, likely due to reduced business and a lack of night-shift staff. Those patients who arrive by ambulance are considered more urgent, and thus pass faster from triage to PIA, but their mean length of stay is also longer. Finally, older patients were found to transition more slowly from triage to PIA and PIA to discharge, which they speculated was because thee medical needs of older patients are more complex than those of younger patients. Most of these results are congruent with the present analysis. While the present study did not model a PIA to discharge transition, it was also found that patients presenting at night were seen more slowly (i.e., start to PIA transition) than those presenting during the day. Additionally, it was also found that patients arriving by ambulance were seen faster, and that older patients moved more slowly through the ED for most transitions. In a study of one Thai ED, Chaou et al. (2020) found that patients with lower acuity are discharged more quickly that those with more urgent acuity scores, but they must wait longer to see physicians and for admission (if necessary). This finding is unsurprising, and mirrors the current study. Chaou et al. (2020) also found that older patients were seen more quickly, which is contrary to the findings of Rizk et al. (2021) and the current study. Similar to Rizk et al. (2021), Chaou et al. (2020) also found that patients presenting at night waited longer to be seen.

The results of the present study are quite comparable to a similar study also using the NACRS dataset. Kroetch et al. (2021) analyzed all pediatric presentations for asthma in Alberta, and found that for the start to PIA transition, higher acuity and ambulance arrival were associated with shorter wait times, while metropolitan/tertiary ED locations were associated with longer times. For the PIA to disposition transition, they found that higher acuity, ambulance arrival and metropolitan/tertiary ED locations were all associated with longer transition times, while presenting during the evening shift resulted in a faster transition. Kroetch et al. (2021) also investigated covariates associated with the disposition to departure transition, which is something the present study did not analyze. Aside from the result relating to evening shift, the findings from Kroetch et al. (2021) are in line with those from the present study.

This study has several limitations. Many of the presentation cases were missing time data, which limited their use in multi-state modelling. Moreover, other patient-related data was not available through NACRS. Additional data that would have been useful to have include a reliable indicator of homelessness, patient involvement in rehab or another treatment program, as well as racial ethnicity. Indeed, Canada has been the subject of recent critique concerning their disregard for racial disparities in health outcomes (Ahmed et al., 2021). Other limitations include potential regional differences in ICD-10 coding and limited numbers of individuals that LWBS, which prohibited the modelling of this transition.

Considering the radical impact of the recent COVID-19 pandemic on health care systems, future research in this area should focus on comparing the results from the current study to data collected during the COVID-19 pandemic. Additionally, future studies should seek to understand the underlying explanations for why patient municipality is able to exert such a profound effect on ED transition times.

In summary, many characteristics relating to both the patient themselves and their ED presentation were found to have a significant influence over the way they moved through the various stages of the ED. Chief among these were acuity/triage score and patient municipality type. These results are mostly in agreeance with those found by other authors in other patient sub-populations. A distinctive feature of the present study is the inclusion of substance type as a covariate in modelling, which was also found to exert significant effects. The present analysis presents a thorough account of patient flow through the ED for an important subgroup of patients, and should be used to inform future policy and research.

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A NACRS & Pampalon Variables

The NACRS dataset contains many more variables than are shown here. This table shows the variables that were extracted from the NACRS dataset for the purposes of the current analysis. Pampalon index variables were calculated using NACRS variables and information from other external sources.

Table 15: Selected NACRS variables.

Field Name	Definition/Description
ABSTRACT_TYPE	Type of patient visit
ADMIT_DATETIME	The calendar date and time when the patient was admitted to an Inpatient Unit into the same facility
ADMIT_DATE_ID	The calendar date when the patient was admitted to an Inpatient Unit into the same facility
ADMIT_TIME_ID	The time when the patient was admitted to an Inpatient Unit into the same facility
ARRIVAL_DATETIME	The calendar date, in year, month and day order, and time, in hours and minutes when the patient arrives at the ED for services
ARRVL_MODE_CD	Mode of arrival code
ARRVL_MODE_NM	Mode of arrival code short description
LEFT_ED_DATETIME	The time, in hours and minutes, when the patient physically leaves the emergency department and does not return during the encounter
LOS_ED_MIN	Length of stay is calculated in minutes between a Start Time and End Time where the Start Time is the earliest of either the ED Triage Time or the ED Visit (Registered). Time as recorded on the ED record and the End time = the Discharge/Time from ED
REG_DATETIME	The calendar date and time the patient was registered (clerked) in ED
REG_DATE_ID	The calendar date the patient was registered (clerked) in ED
REG_TIME_ID	The time the patient was registered (clerked) in ED
ADMITBYAMB	Type of ambulance if the patient arrives at the hospital by ambulance
AGE_ADMIT	Patient age in years as calculated at admission
DISP_DATE or DISP_DATE_DT or DISP_DTAE_SRC	Date when the main service provider makes the decision about the patient's disposition
DISP_DTTM	Date and time when the main service provider makes the decision about the patient's disposition
DISP_TIME or DISP_TIME_SRC	Time when the main service provider makes the decision about the patient's disposition
DISPOSITION	Type of separation from the service at the end of each visit
DXCODE Up to 10 occurrences	ICD-10-CA diagnosis code that describes the diagnoses/ conditions/problems/circumstances of the patient during the length of stay in the health care facility
ED_DEPT_DATE or ED_DEPT_DATE_DT or ED_DEPT_DATE_SRC	Date when the patient physically leaves the ED and does not return

ED_DEPT_DTTM	Date and time when the patient physically leaves the ED and does not return
ED_DEPT_TIME or ED_DEPT_TIME_SRC	Time when the patient physically leaves the ED and does not return
ED_ER_MINUTES	ED length of stay in minutes for patients who are admitted.
EIP_MINUTES	Inpatient length of stay in minutes for ED patients who are admitted.
ED_VISIT_INDICATOR	0 = Not an ED visit - Scheduled visits to the emergency department where the visit date and time are fixed and the appointment is recorded in a scheduling system (electronic or manual) 1 = ED visit - Visits to the emergency department where the presentation does not fall into category 0—“Not an ED visits”.
FISCAL_YR	Fiscal year of reporting period determined by visit date.
GENDER	Gender of patient
INST or Facility ID	The institution number is a 5-digit code assigned to a reporting facility by AHW identifying the facility and the level of care for the data submitted.
INST_REG	Region number of the facility according to RHA boundaries set by AHW in December 2003.
INST_ZONE	Zone of the facility according to boundaries set by AHS.
INSTFROM	Patient is directly transferred from another health care facility for further treatment/care.
INSTTO	Healthcare facility or another level of care within the reporting facility where the patient is transferred to
PC_ABBREV	2-character alpha code based on a coding system developed by CIHI.
PC_KNOWN	Yes/No flag that indicates availability of service recipient’s place of residence postal code
PIA_DTTM	Date and time of Physician Initial Assessment
PIA_DATE or PIA_DATE_DT or PIA_DATE_SRC	Date the first physician assessed the patient
PIA_TIME or PIA_TIME_SRC	Time the first physician assessed the patient
POSTCODE	Full postal code
RCPT_LOCAL	Building blocks for the provincial health boundaries introduced in 2011, containing 132 entities and a minimum population of 5000.
RCPT_REG	Region of residence of the patient according to RHA boundaries set by AHW in December 2003.
RCPT_ZONE	Zone of residence of the patient according to boundaries set by AHS.
RESNAME	The geographic area in which the client resides
SCHEDULED_ED	Indicates when day surgery or outpt clinic visits take place in the ED
TRIAGE_DATE or TRIAGE_DATE_DT or TRIAGE_DATE_SRC	Date when the client was triaged in the emergency department
TRIAGE_DTTM	Date and time when the client was triaged in the emergency department
TRIAGE_TIME or TRIAGE_TIME_SRC	Time when the client was triaged in the emergency department
TRIAGECODE	Level of triage for the client on this visit

VISIT_DATE or VISIT_DATE_DT or VISIT_DATE_SRC	Date when the client presented for services to any ambulatory care functional centre and is officially registered as a patient
VISIT_DTTM	Date and time when the client presented for services to any ambulatory care functional centre and is officially registered as a patient
VISIT_LOS_MINUTES	Total length of stay in minutes for the patient's visit
VISIT_TIME or VISIT_TIME_SRC	Time that the client was registered at the facility on the day of the visit
VISIT_TYPE	Used to differentiate between planned and unplanned visits to an Emergency Department

Table 16: Selected Pampalon variables.

Field	Description/definition	Data source
Urban	Urban/rural status for Local Geography Boundaries. Created by examining population densities and travel times to a variety of health services. (Example: MODERATE METRO INFLUENCE).	Pampalon Index
DApop2016	Total population of the dissemination area	Pampalon Index
income	Average income of people aged 15 years and older	Pampalon Index

B Relevant ED Codes

B.1 F codes

- F10. – Mental and behavioural disorders due to use of alcohol
- F11. – Mental and behavioural disorders due to use of opioids
- F12. – Mental and behavioural disorders due to use of cannabinoids
- F13. – Mental and behavioural disorders due to use of sedative hypnotics
- F14. – Mental and behavioural disorders due to use of cocaine
- F15. – Mental and behavioural disorders due to use of other stimulants, including caffeine
- F16. – Mental and behavioural disorders due to use of hallucinogens
- F17. – Mental and behavioural disorders due to use of tobacco
- F18. – Mental and behavioural disorders due to use of volatile solvents
- F19. – Mental and behavioural disorders due to multiple drug use and use of other psychoactive substances
  - .0 = antidepressants
  - .1 = laxatives
  - .2 = analgesics
  - .3 = antacids
  - .4 = vitamins
  - .5 = steroids/hormones
  - .6 = herbal/folk remedy
  - .7 = *DNE
  - .8 = Other
  - .9 = Unspecified

B.2 T codes

- T40. - Poisoning by narcotics and psychodysleptics
  - .0 = opium
  - .1 = heroin
  - .2 = other opiods (ex. codeine, morphine)
  - .3 = methadone
  - .4 = other and synthetic narcotics (ex. pethidine)
  - .5 = cocaine
  - .6 = other unspecified narcotics
  - .7 = cannabis (and derivatives)
  - .8 = lysergide (LSD)

  - .9 = other and unspecified psychodysleptics/hallucinogens (ex. mescaline, psilocin, psilocybine, etc.)

- T41. - poisoning by anaesthetics and therpeutic gases (pick and choose here)
  - .0 = inhaled anaesthetics (excluding oxygen)
  - .1 = intravenous anaesthetics (ex. thiobarbiturates)
  - .2 = other and unspecified general anaesthetics
  - .3 = local anaesthetics
  - .4 = unspecified anaesthetics
  - .5 = therapeutic gases (carbon dioxide, oxygen)
- Other T codes - please consult https://icd.who.int/browse10/2010/en#/T36

C Disposition Codes

- 06 - admit to "reporting facility" as an inpatient to a special care unit, critical care unit or operating room
- 07 - admit to reporting facility as an inpatient to some other unit in the hospital
- 08 - transfer to another acute care facility
- 09 - transfer to another non-acute care facility (stand-alone rehab, mental health centre, etc.)
- 12 - within-facility transfer to day surgery
- 14 - within-facility transfer to clinic
- 16 - discharge to private home (or apartment) with supports/referral
- 17 - discharge to private home (or apartment) without supports/referral
- 30 - transfer to long-term care (i.e., mental health, 24-hour nursing, addiction treatment centre, or palliative care facility)
- 40 - transfer to assisted/group living, including shelters (these do not have 24-hour nursing care)
- 61 - patient left after registration (triage or treatment did not occur)
- 62 - patient left against medical advice after initial treatment had began
- 63 - patient left against medical advice after triage but before treatment
- 64 - patient left after PIA but before treatment
- 72 - patient died in the facility (excludes suicide/medically-assisted suicide)
- 90 - patient transferred to jail or halfway house

D KM Curves by Covariate

Some of the following plots may not begin at a proportion of 1. This is because instantaneous transition times were not removed.

D.1 Start to PIA (State 1 - 2)

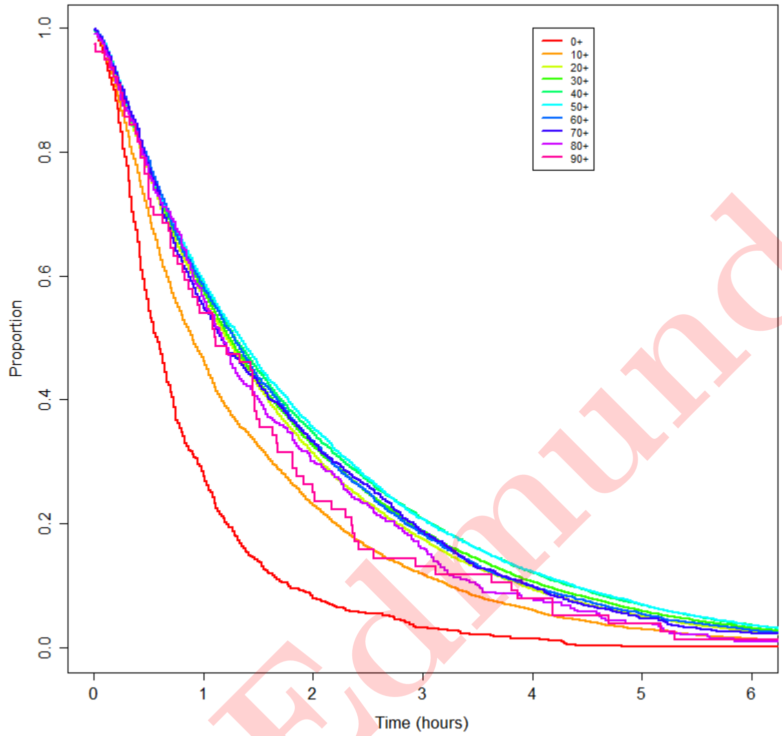

Figure 24: Kaplan-Meier curve for the Start to PIA transition (State 1 - 2), separated by age.

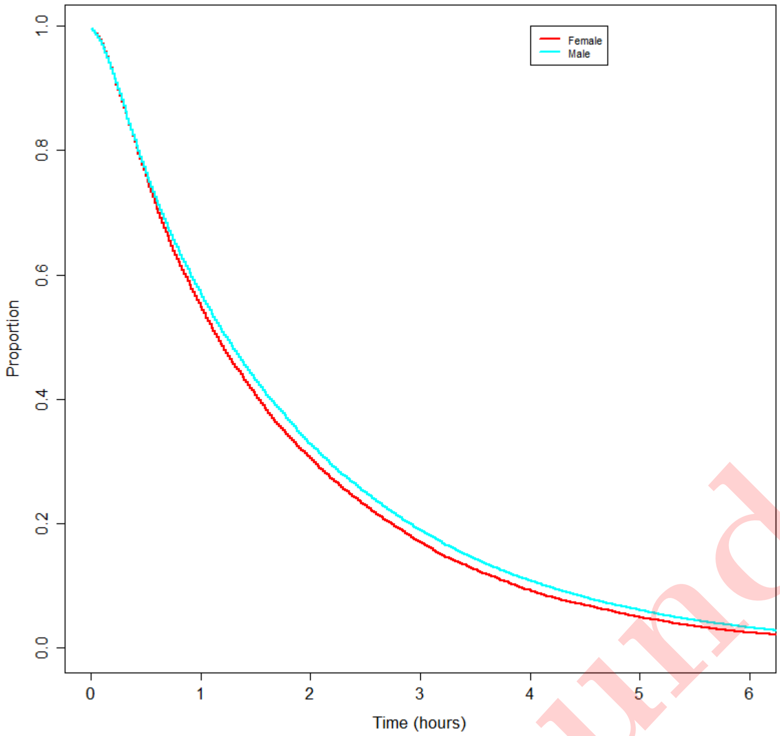

Figure 25: Kaplan-Meier curve for the Start to PIA transition (State 1 - 2), separated by gender.

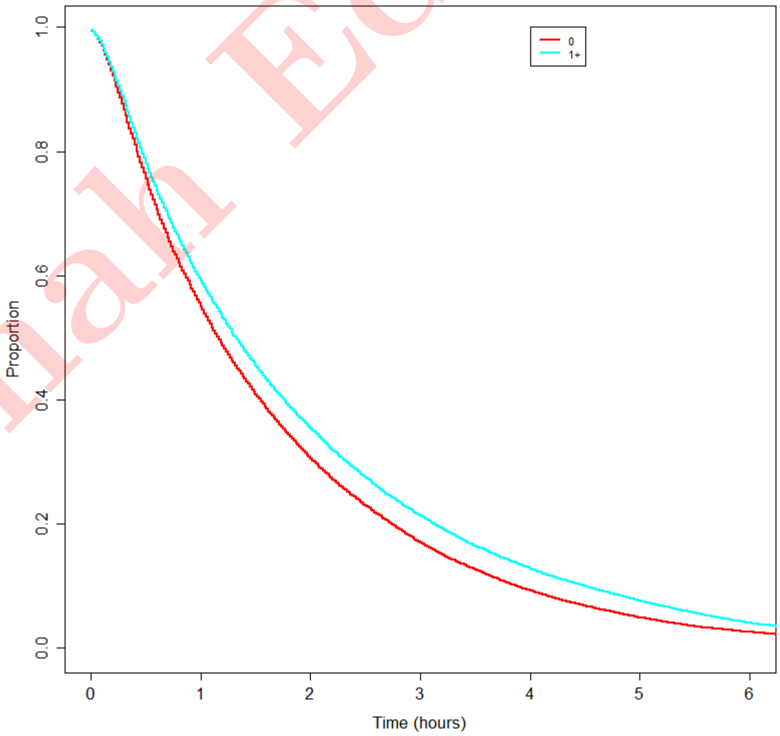

Figure 26: Kaplan-Meier curve for the Start to PIA transition (State 1 - 2), separated by Charlson index score.

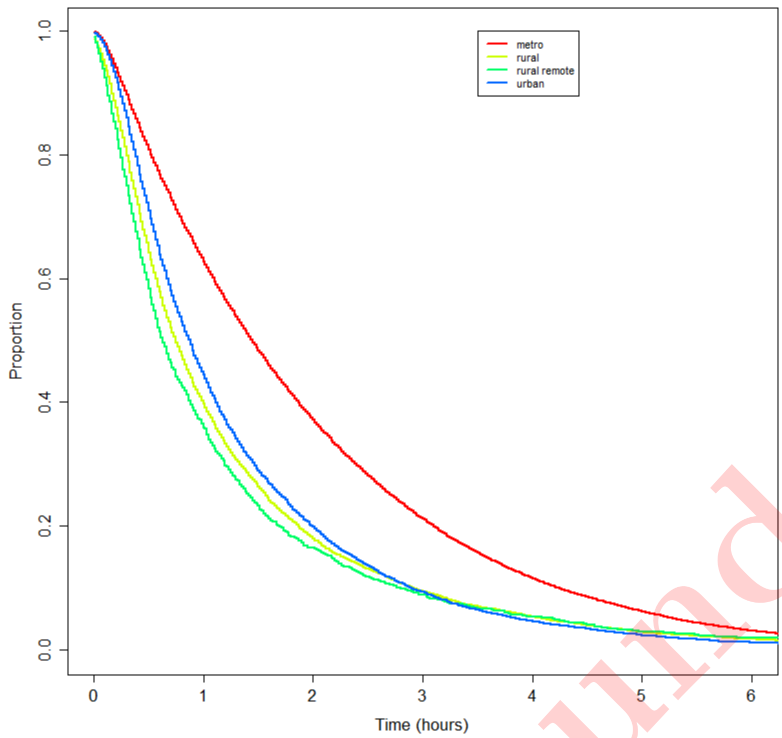

Figure 27: Kaplan-Meier curve for the Start to PIA transition (State 1 - 2), separated by patient municipality.

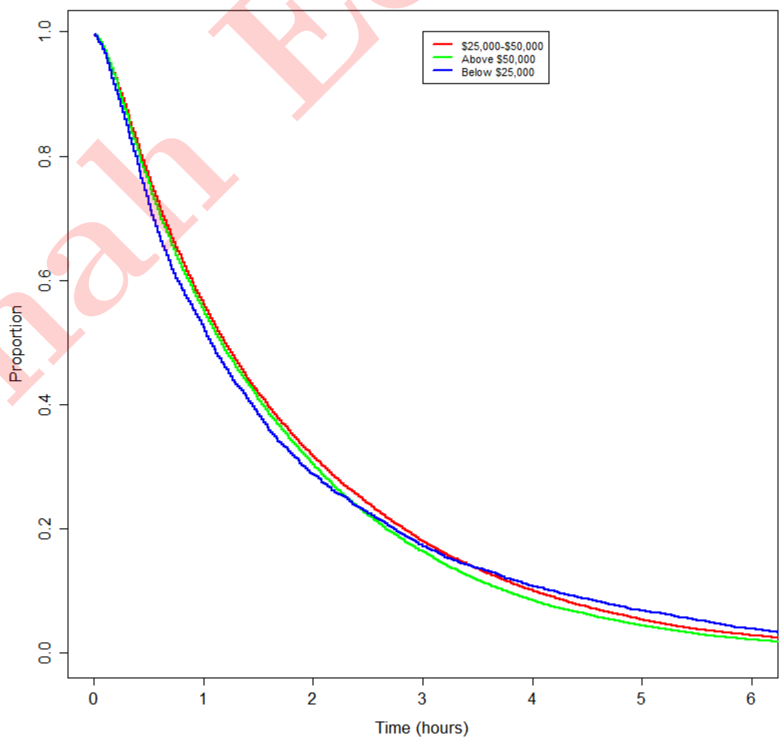

Figure 28: Kaplan-Meier curve for the Start to PIA transition (State 1 - 2), separated by patient income.

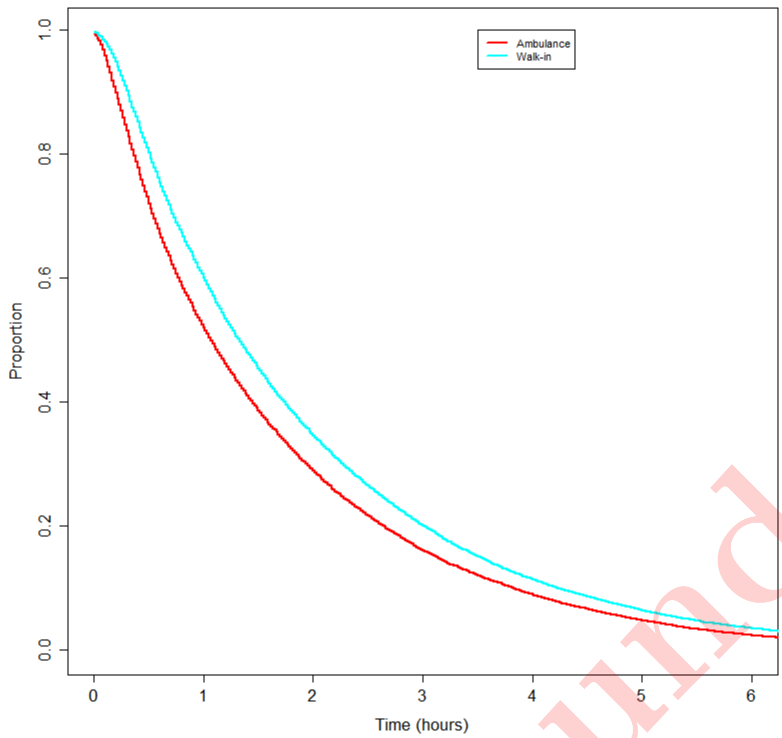

Figure 29: Kaplan-Meier curve for the Start to PIA transition (State 1 - 2), separated by arrival type.

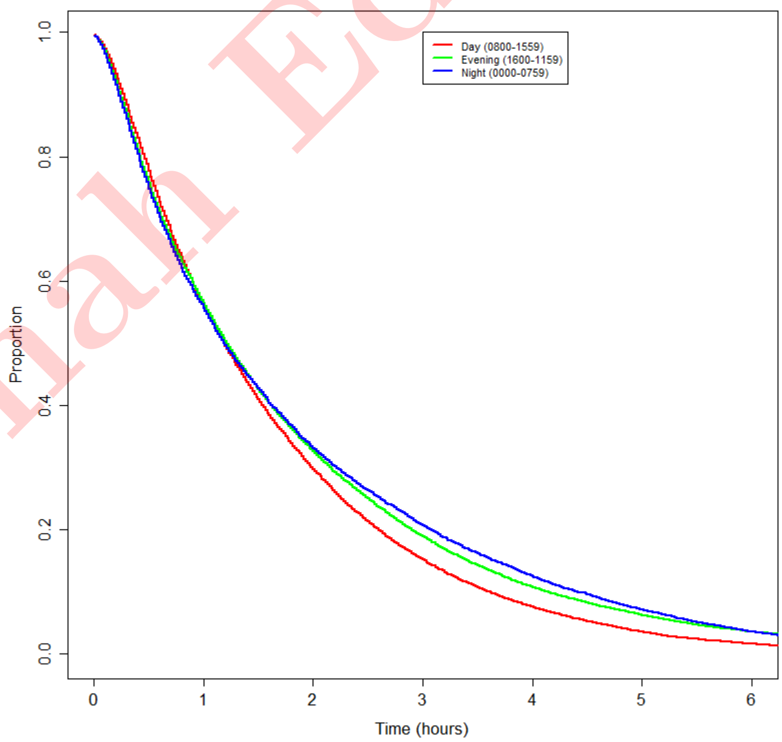

Figure 30: Kaplan-Meier curve for the Start to PIA transition (State 1 - 2), separated by time of arrival.

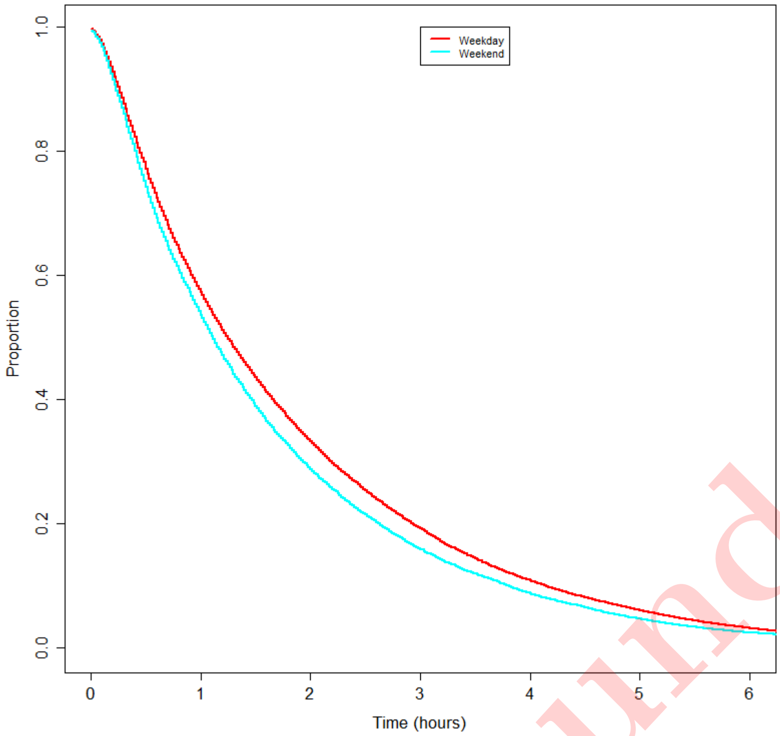

Figure 31: Kaplan-Meier curve for the Start to PIA transition (State 1 - 2), separated by day of the week (weekend or weekday).

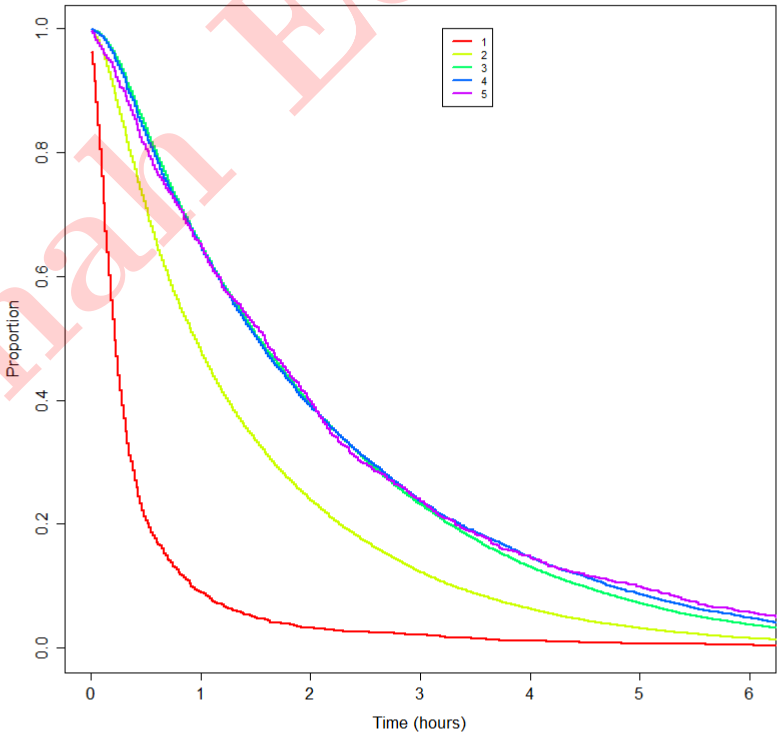

Figure 32: Kaplan-Meier curve for the Start to PIA transition (State 1 - 2), separated by triage score (CTAS).

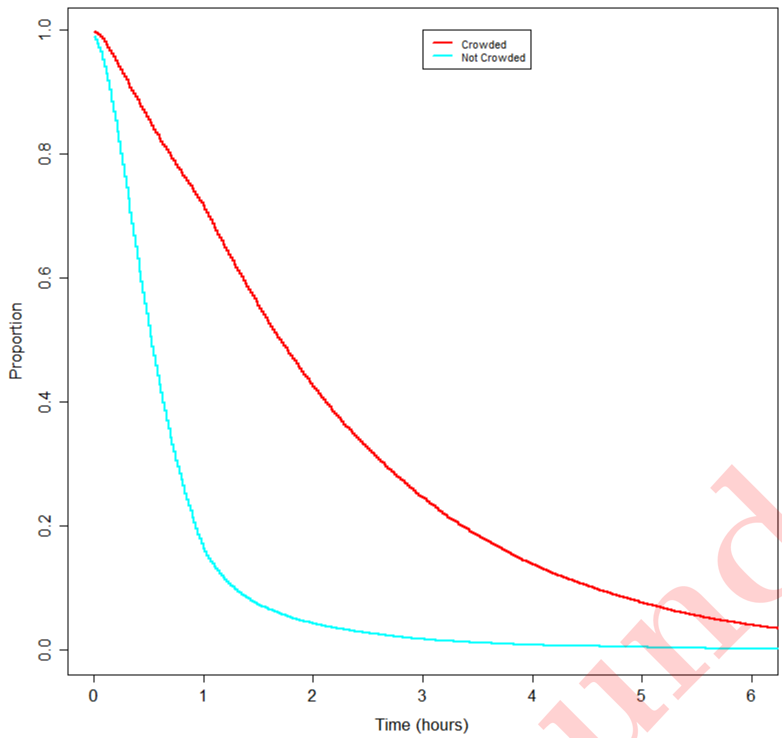

Figure 33: Kaplan-Meier curve for the Start to PIA transition (State 1 - 2), separated by ED crowding status.

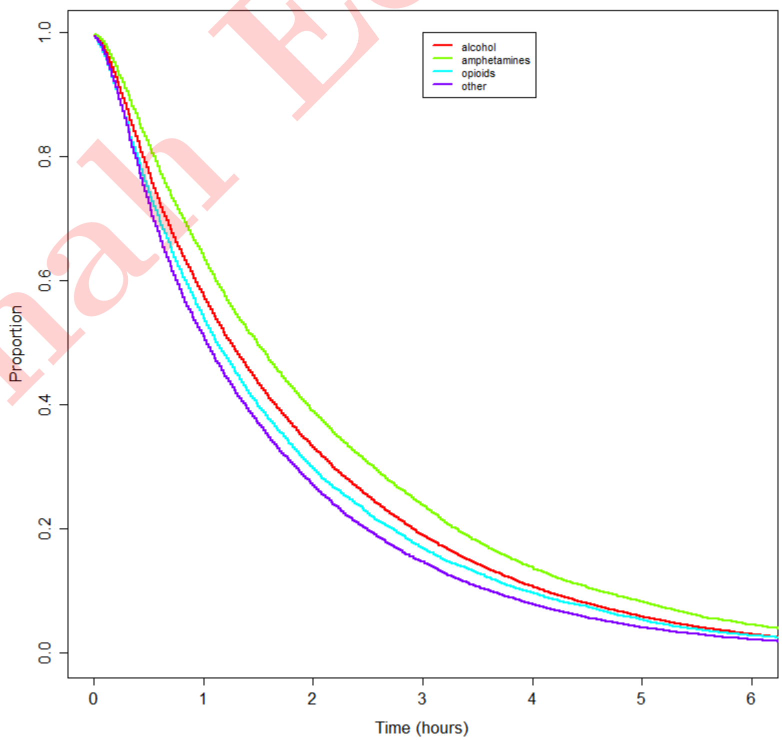

Figure 34: Kaplan-Meier curve for the Start to PIA transition (State 1 - 2), separated by diagnostic code.

D.2 PIA to discharge disposition decision (State 2 - 3)

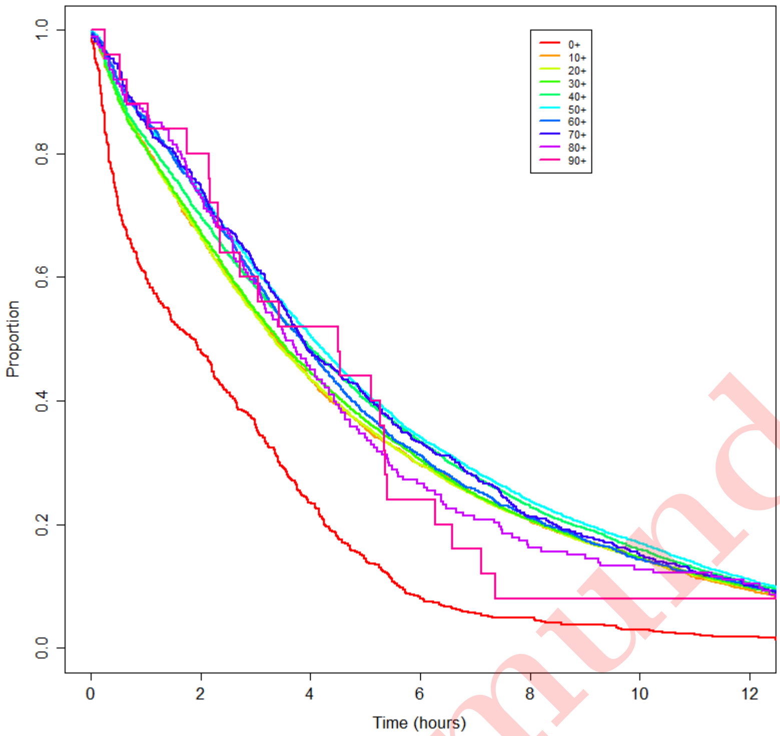

Figure 35: Kaplan-Meier curve for the PIA to discharge disposition decision transition (State 2 - 3), separated by age.

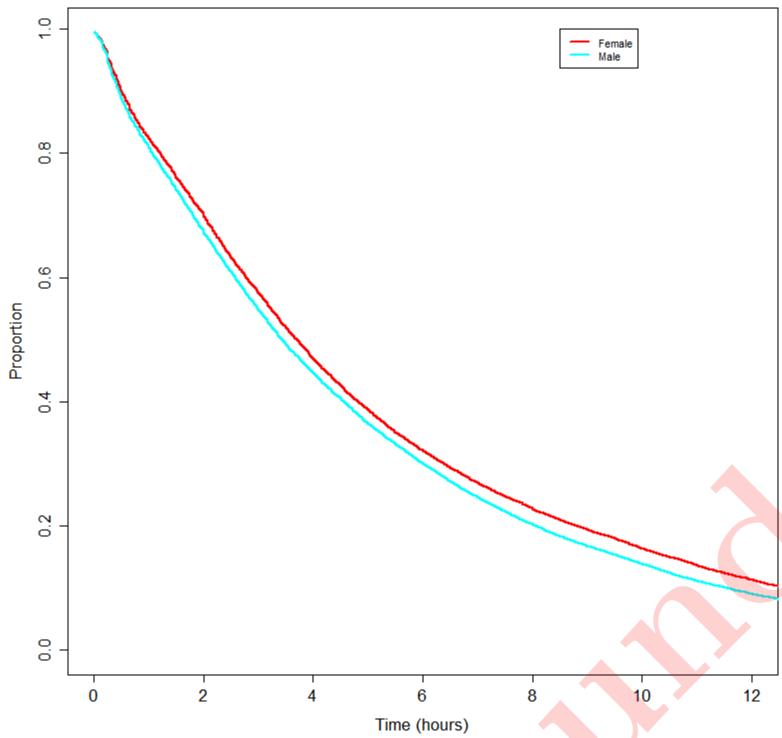

Figure 36: Kaplan-Meier curve for the PIA to discharge disposition decision transition (State 2 - 3), separated by gender.

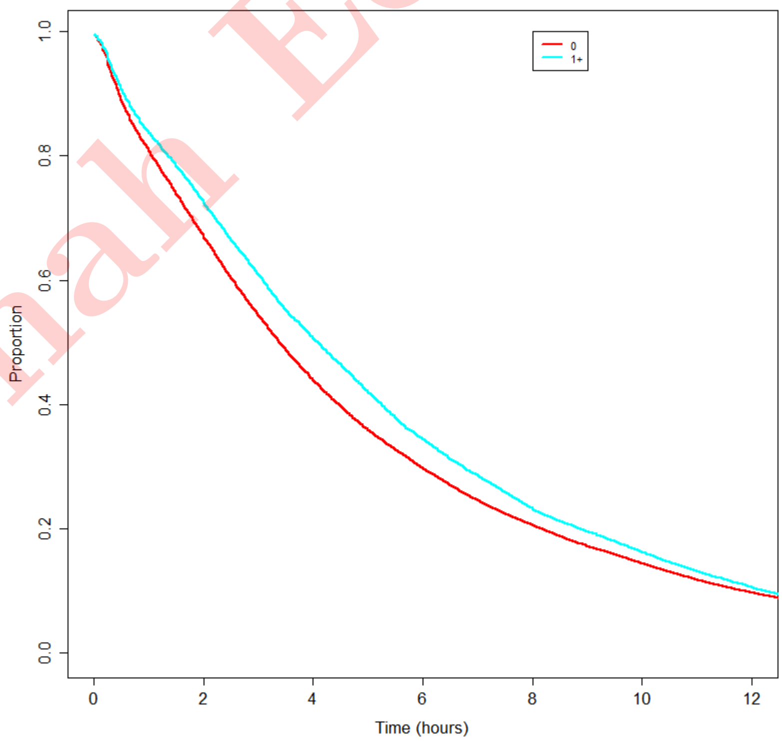

Figure 37: Kaplan-Meier curve for the PIA to discharge disposition decision transition (State 2 - 3), separated by Charlson index score.

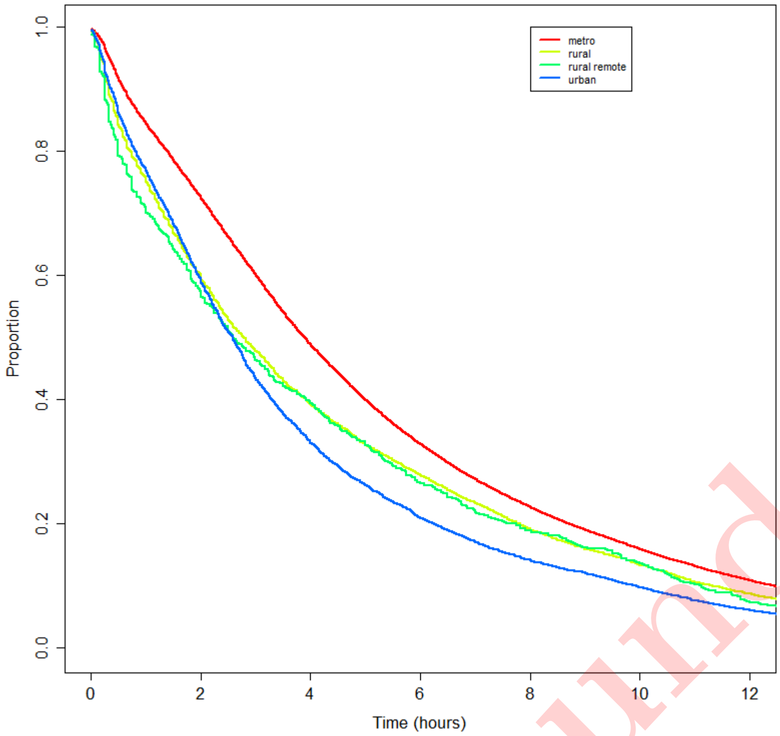

Figure 38: Kaplan-Meier curve for the PIA to discharge disposition decision transition (State 2 - 3), separated by patient municipality.

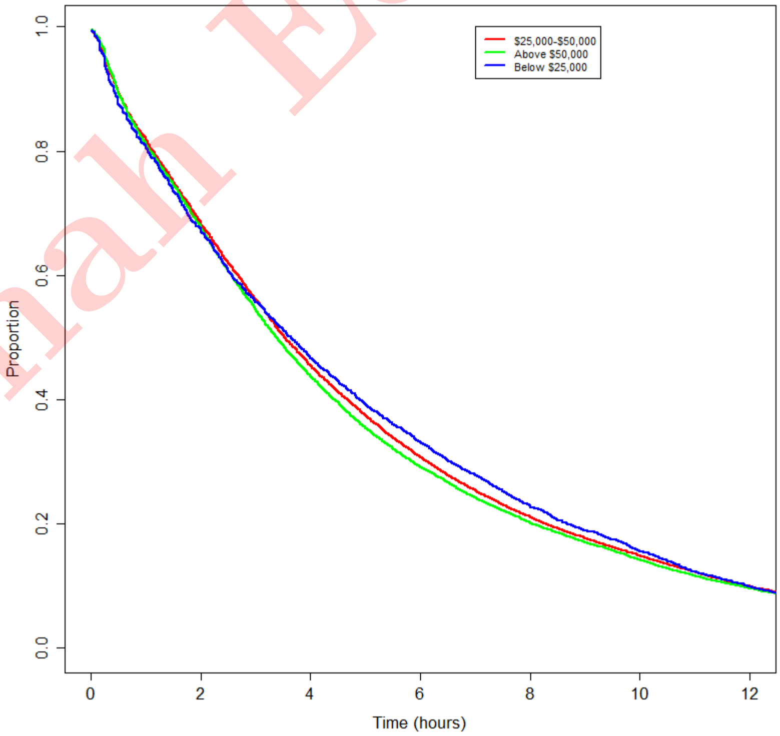

Figure 39: Kaplan-Meier curve for the PIA to discharge disposition decision transition (State 2 - 3), separated by patient income.

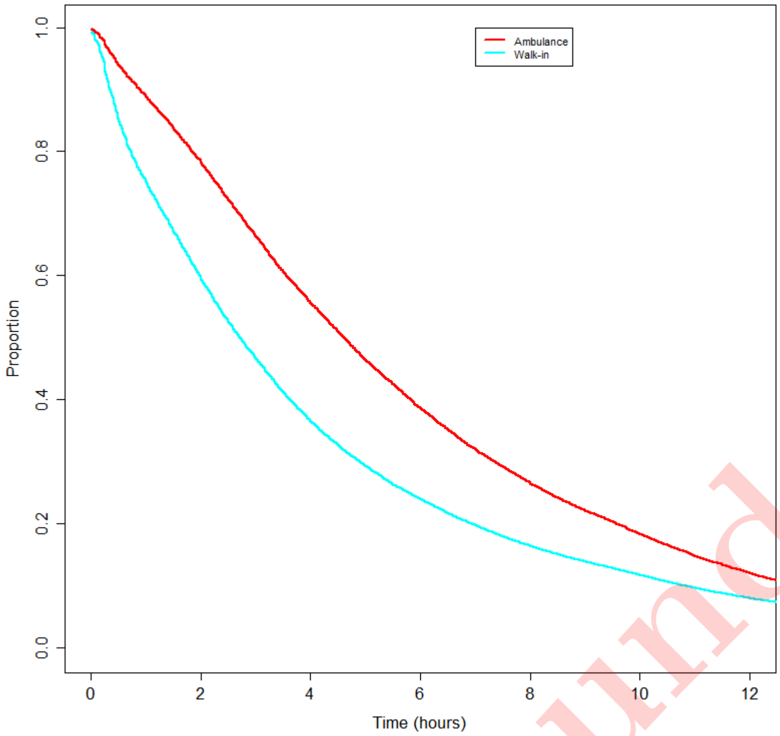

Figure 40: Kaplan-Meier curve for the PIA to discharge disposition decision transition (State 2 - 3), separated by arrival type.

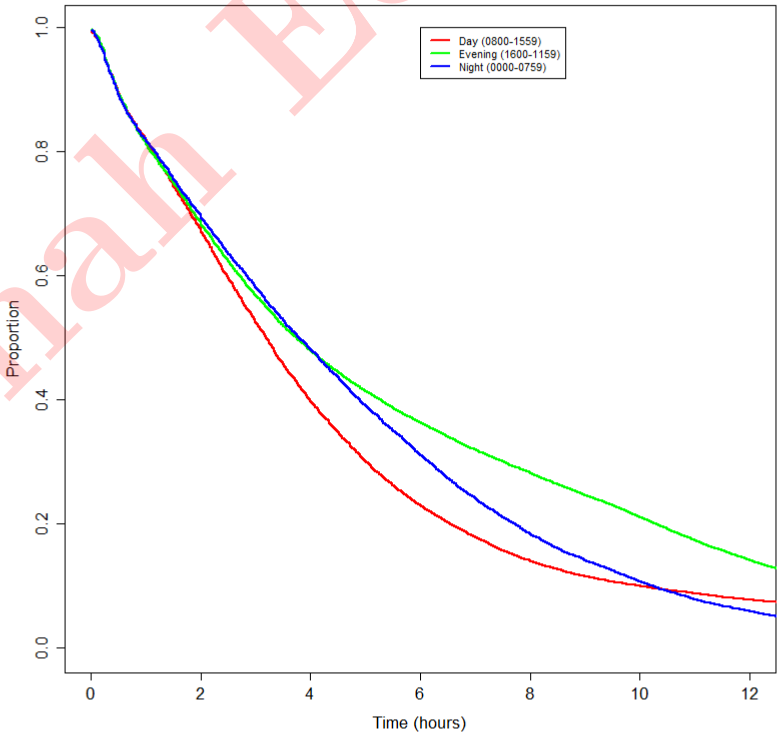

Figure 41: Kaplan-Meier curve for the PIA to discharge disposition decision transition (State 2 - 3), separated by time of arrival.

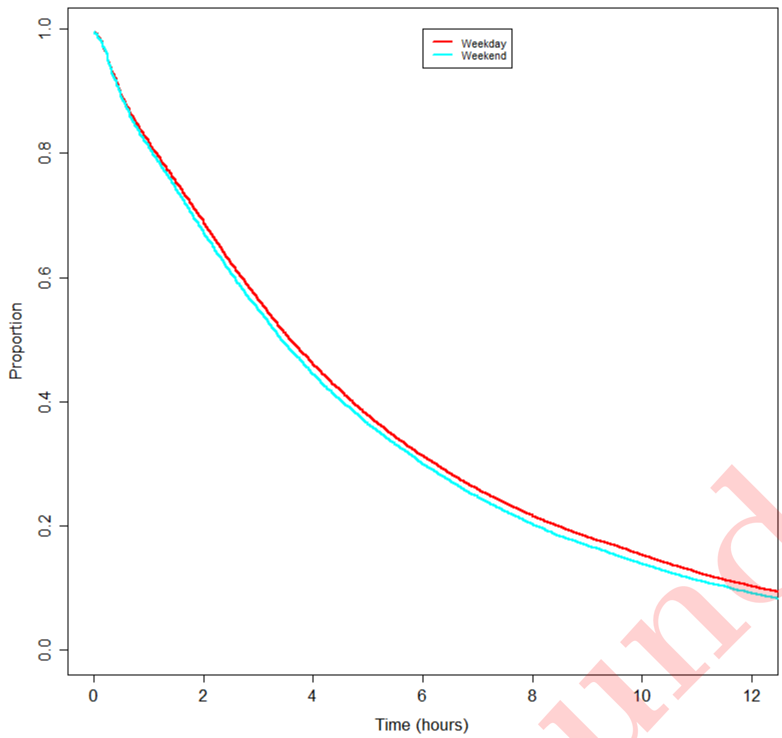

Figure 42: Kaplan-Meier curve for the PIA to discharge disposition decision transition (State 2 - 3), separated by day of the week (weekend or weekday).

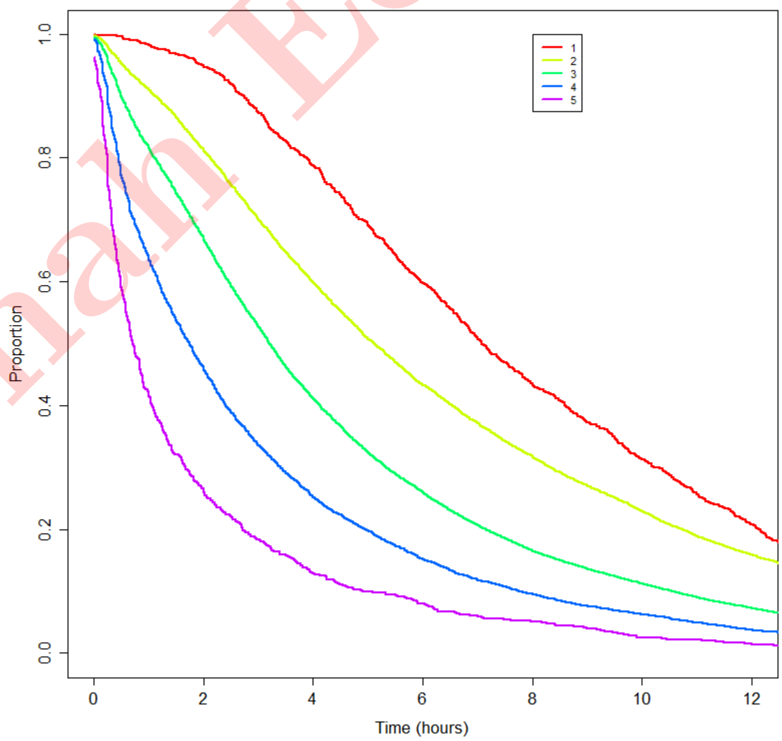

Figure 43: Kaplan-Meier curve for the PIA to discharge disposition decision transition (State 2 - 3), separated by triage score (CTAS).

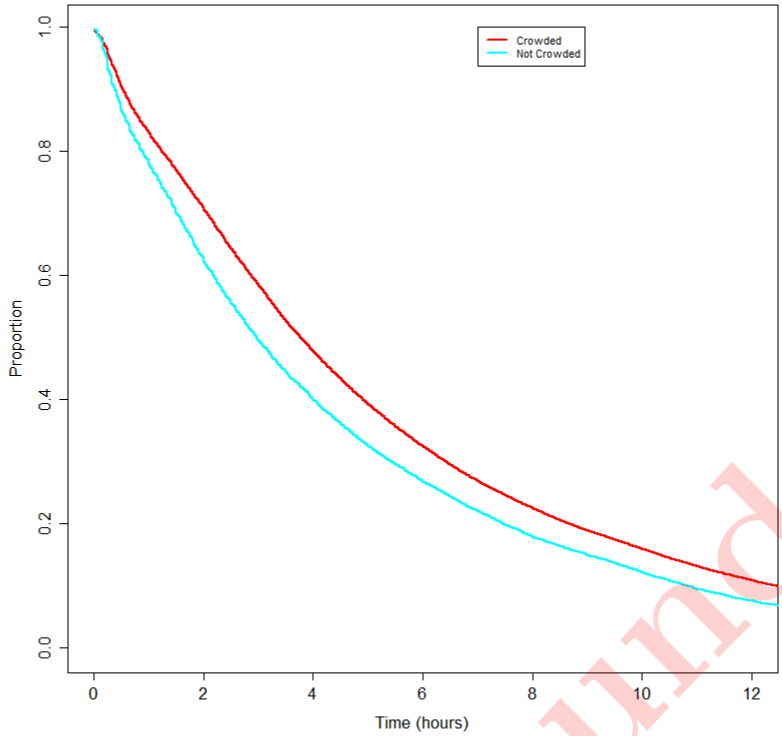

Figure 44: Kaplan-Meier curve for the PIA to discharge disposition decision transition (State 2 - 3), separated by ED crowding status.

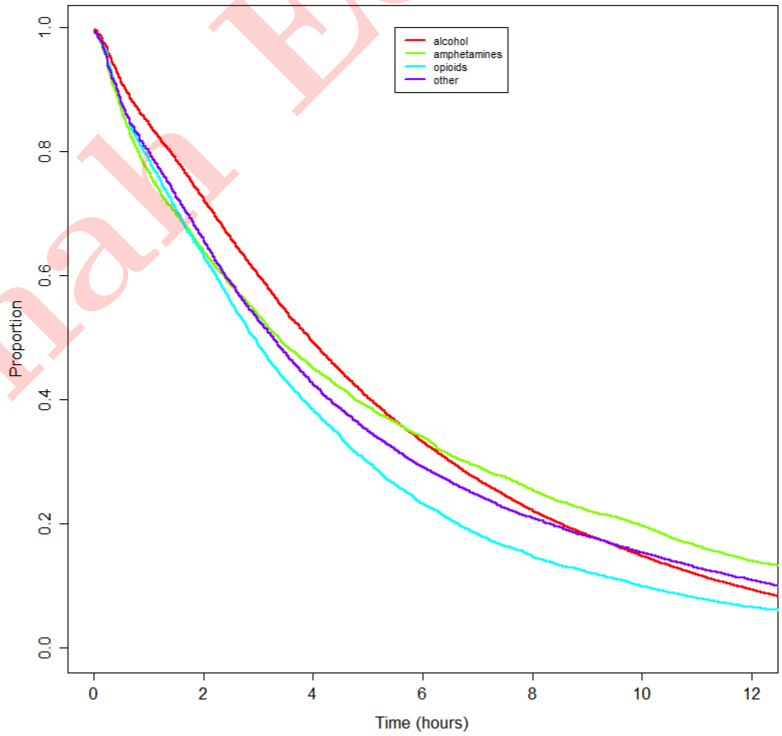

Figure 45: Kaplan-Meier curve for the PIA to discharge disposition decision transition (State 2 - 3), separated by diagnostic code.

D.3 PIA to admit & transfer disposition decision (State 2 - 4)

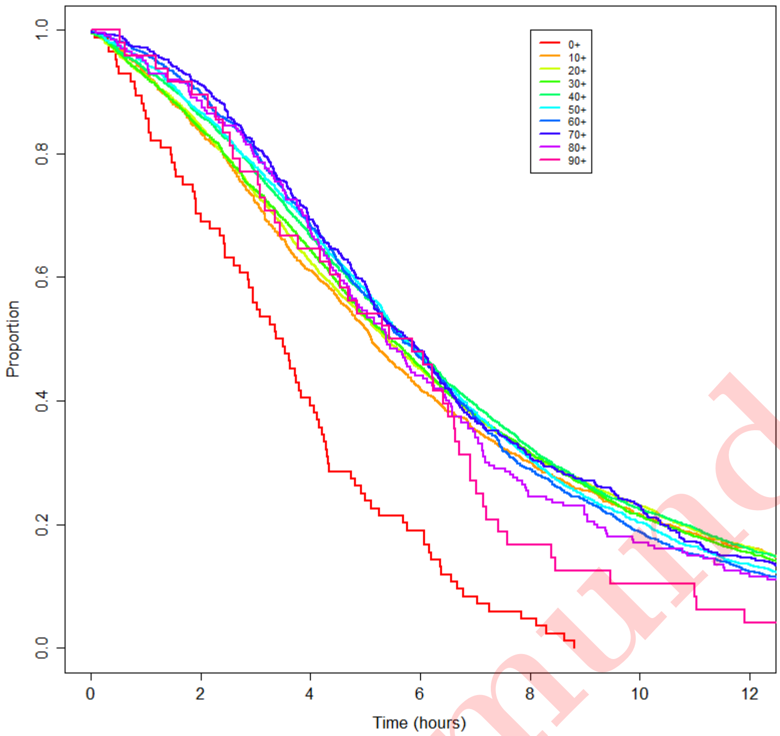

Figure 46: Kaplan-Meier curve for the PIA to admit & transfer disposition decision transition (State 2 - 4), separated by age.

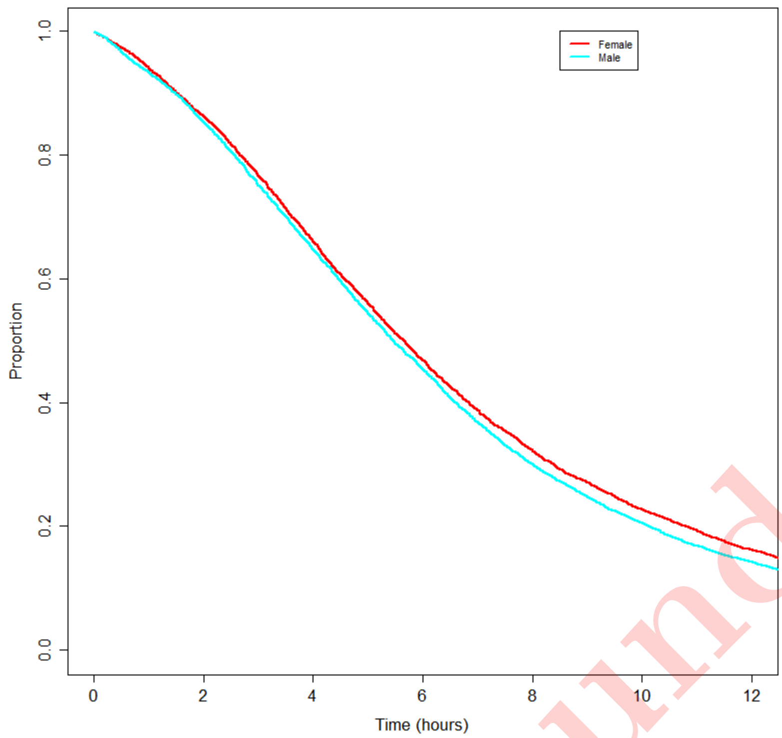

Figure 47: Kaplan-Meier curve for the PIA to admit & transfer disposition decision transition (State 2 - 4), separated by gender.

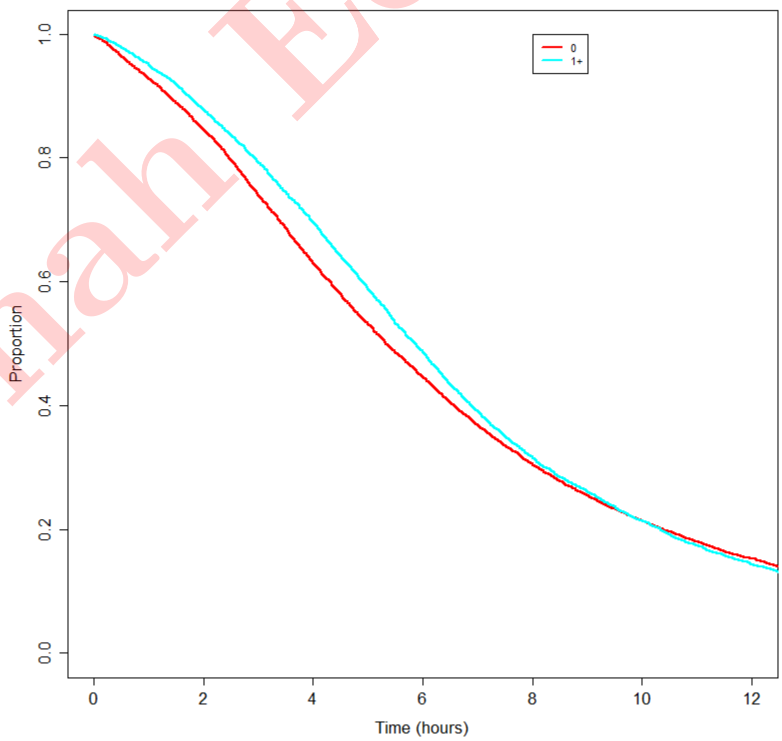

Figure 48: Kaplan-Meier curve for the PIA to admit & transfer disposition decision transition (State 2 - 4), separated by Charlson index score.

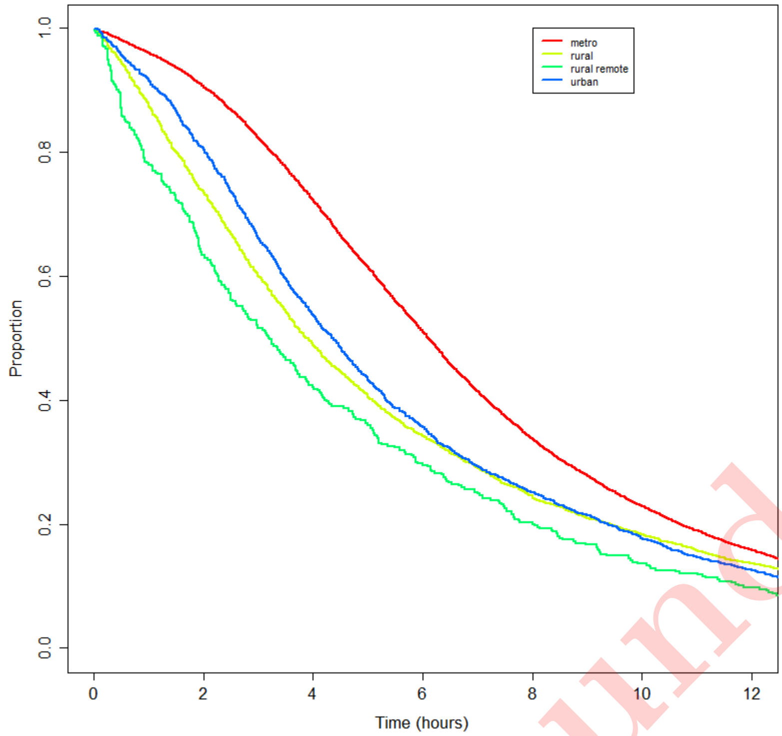

Figure 49: Kaplan-Meier curve for the PIA to admit & transfer disposition decision transition (State 2 - 4), separated by patient municipality.

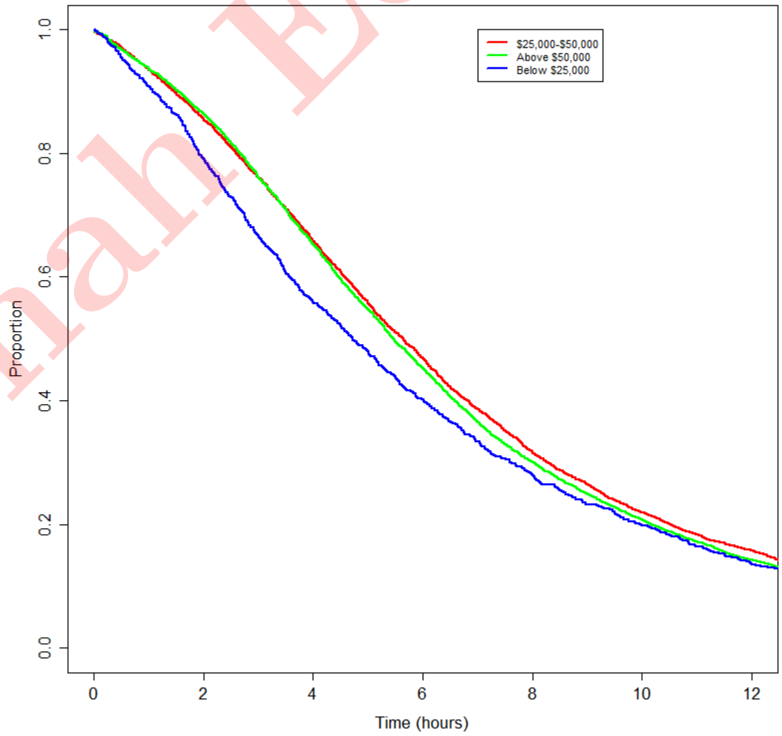

Figure 50: Kaplan-Meier curve for the PIA to admit & transfer disposition decision transition (State 2 - 4), separated by patient income.

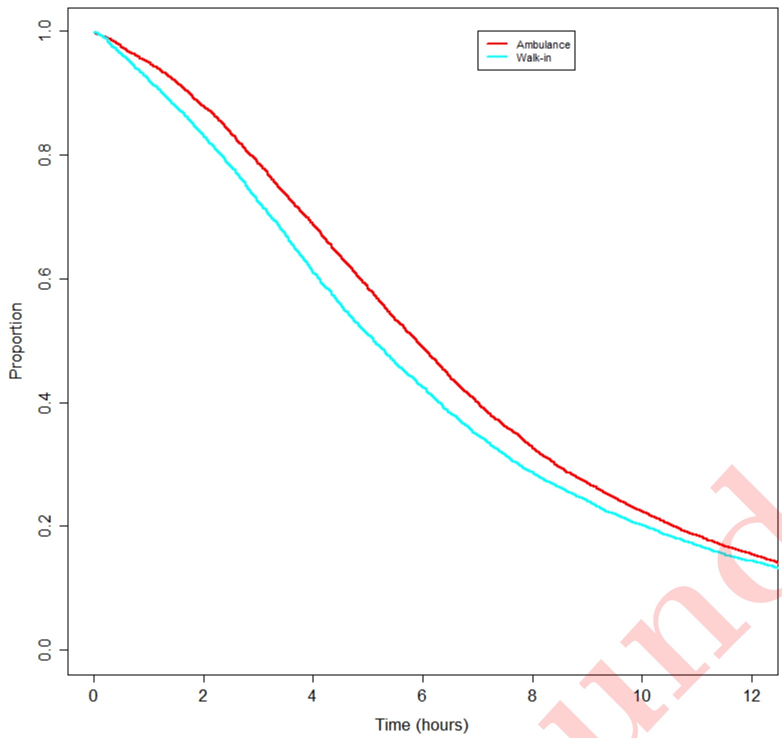

Figure 51: Kaplan-Meier curve for the PIA to admit & transfer disposition decision transition (State 2 - 4), separated by arrival type.

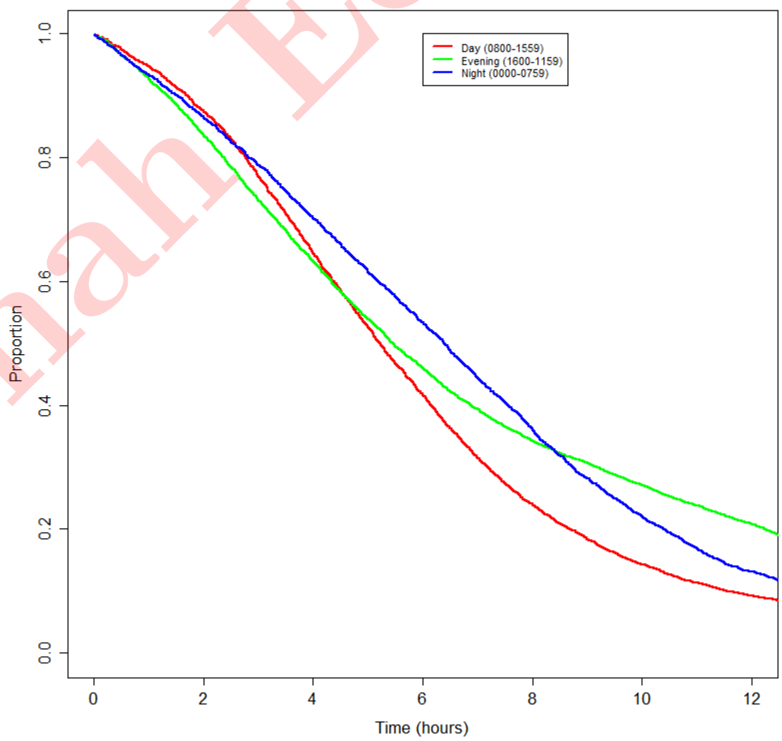

Figure 52: Kaplan-Meier curve for the PIA to admit & transfer disposition decision transition (State 2 - 4), separated by time of arrival.

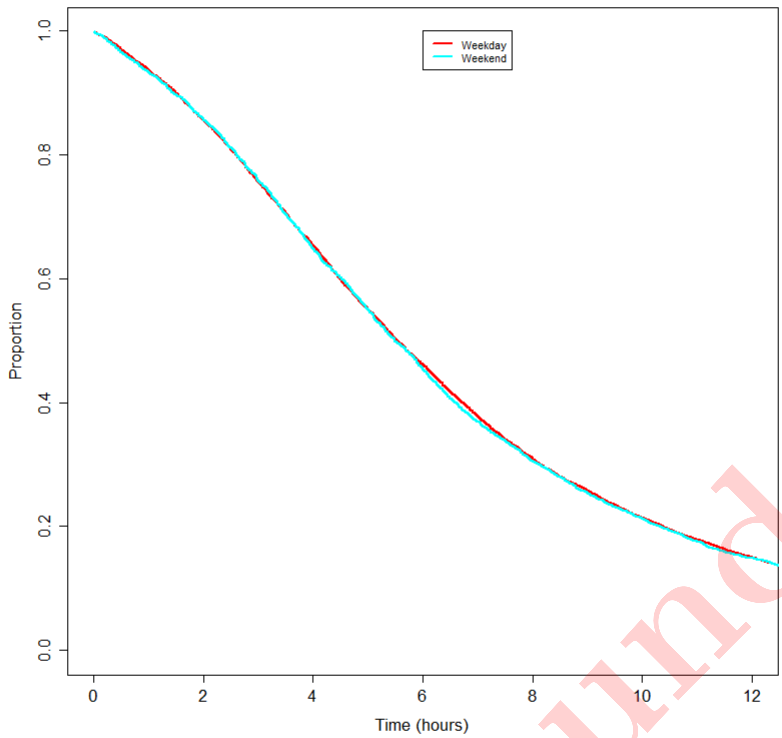

Figure 53: Kaplan-Meier curve for the PIA to admit & transfer disposition decision transition (State 2 - 4), separated by day of the week (weekend or weekday).

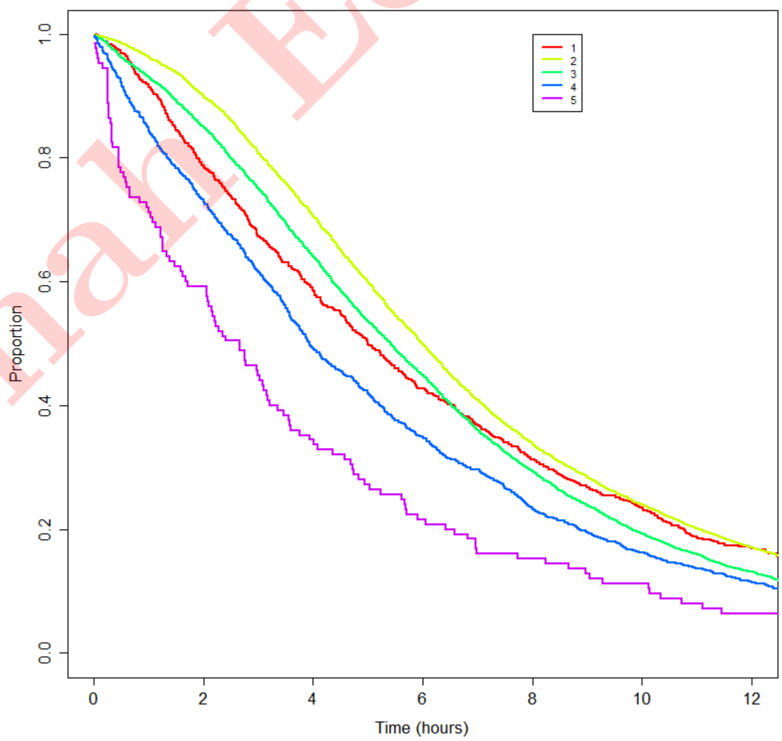

Figure 54: Kaplan-Meier curve for the PIA to admit & transfer disposition decision transition (State 2 - 4), separated by triage score (CTAS).

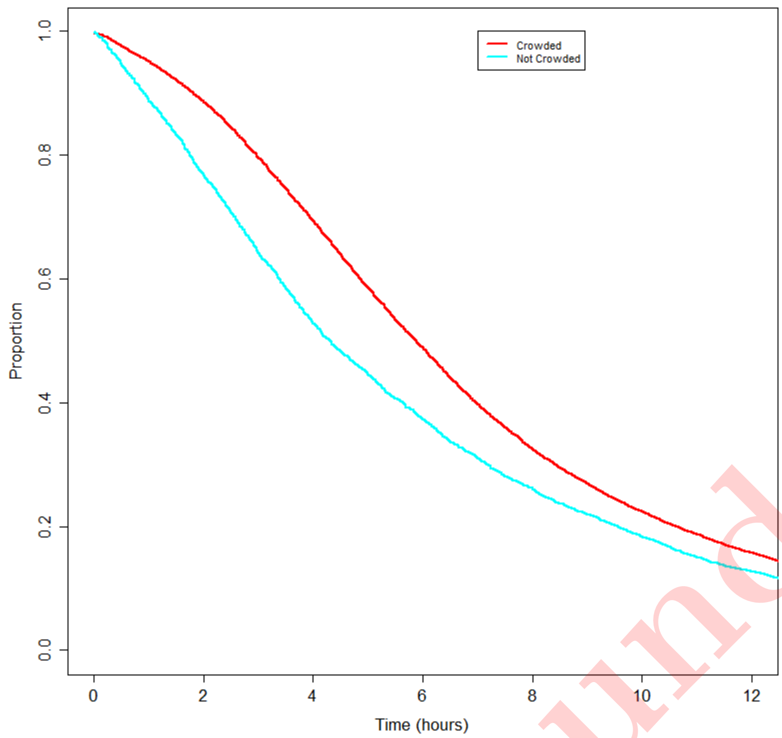

Figure 55: Kaplan-Meier curve for the PIA to admit & transfer disposition decision transition (State 2 - 4), separated by ED crowding status.

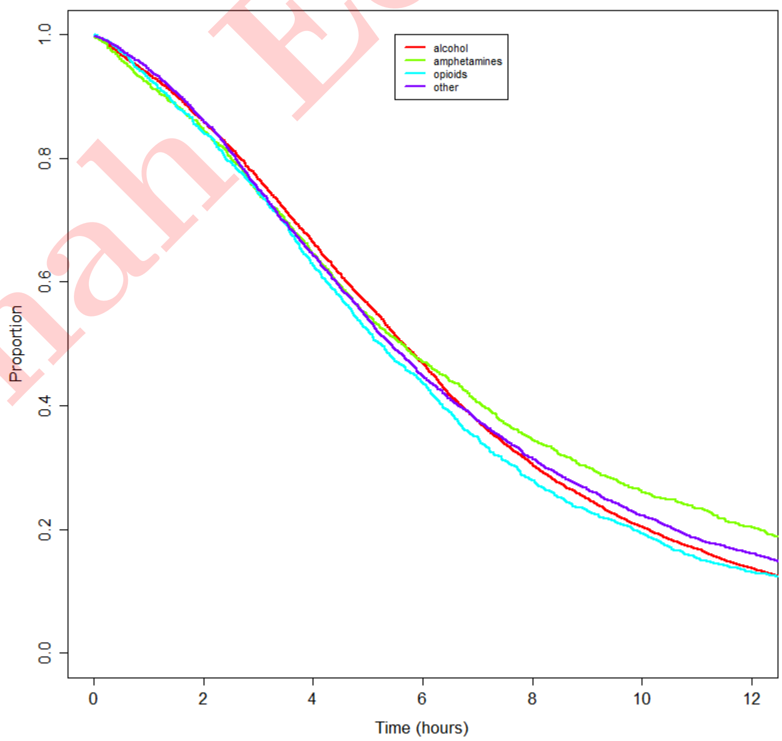

Figure 56: Kaplan-Meier curve for the PIA to admit & transfer disposition decision transition (State 2 - 4), separated by diagnostic code.

D.4 Admit/transfer disposition decision to admission (State 4 - 5)

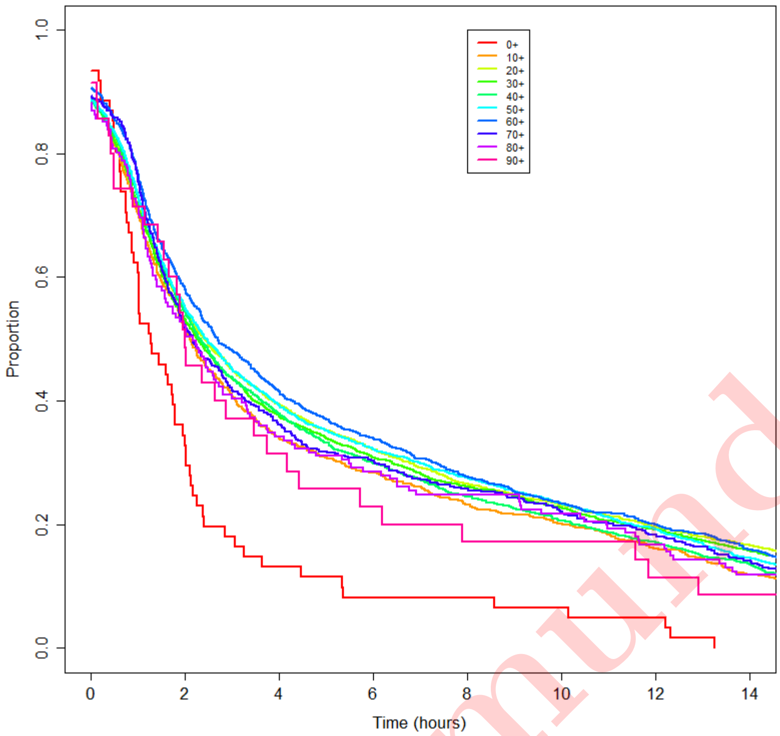

Figure 57: Kaplan-Meier curve for the Admit/transfer disposition decision to admission transition (State 4 - 5), separated by age.

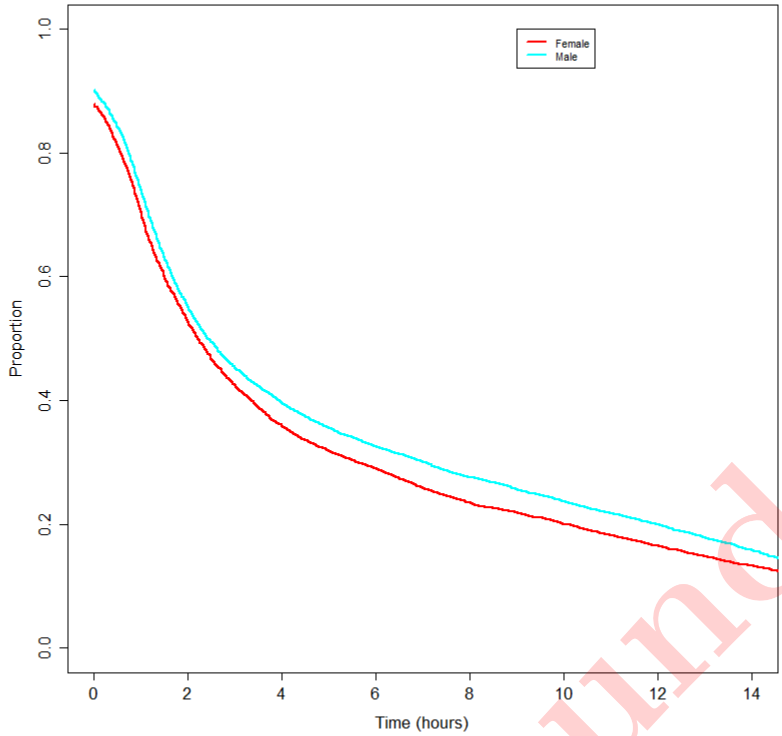

Figure 58: Kaplan-Meier curve for the Admit/transfer disposition decision to admission transition (State 4 - 5), separated by gender.

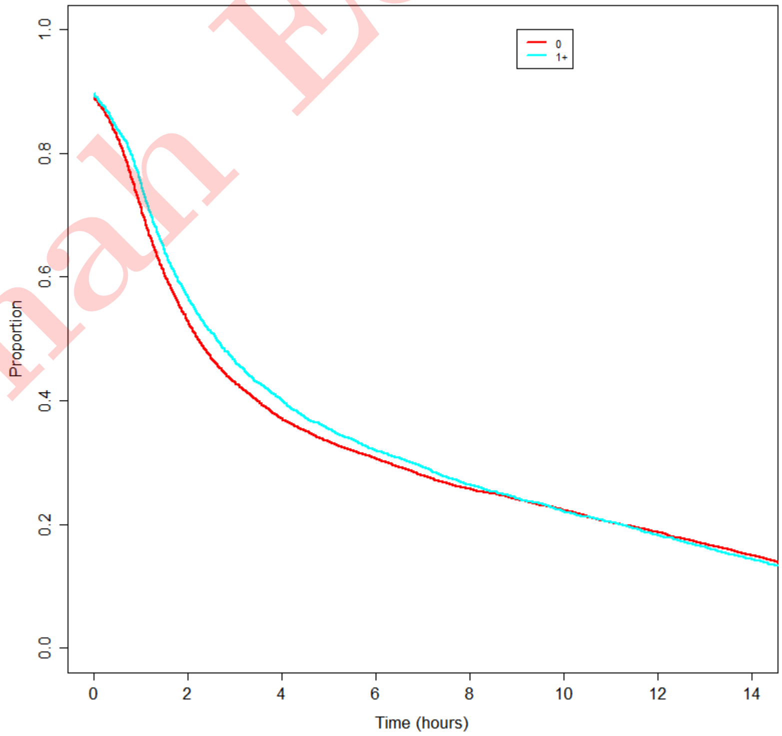

Figure 59: Kaplan-Meier curve for the Admit/transfer disposition decision to admission transition (State 4 - 5), separated by Charlson index score.

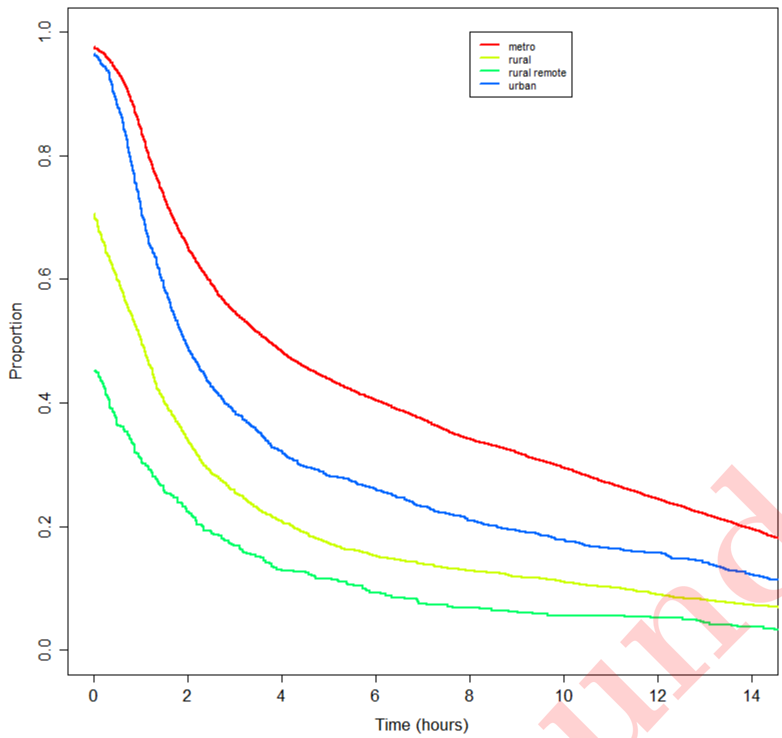

Figure 60: Kaplan-Meier curve for the Admit/transfer disposition decision to admission transition (State 4 - 5), separated by patient municipality.

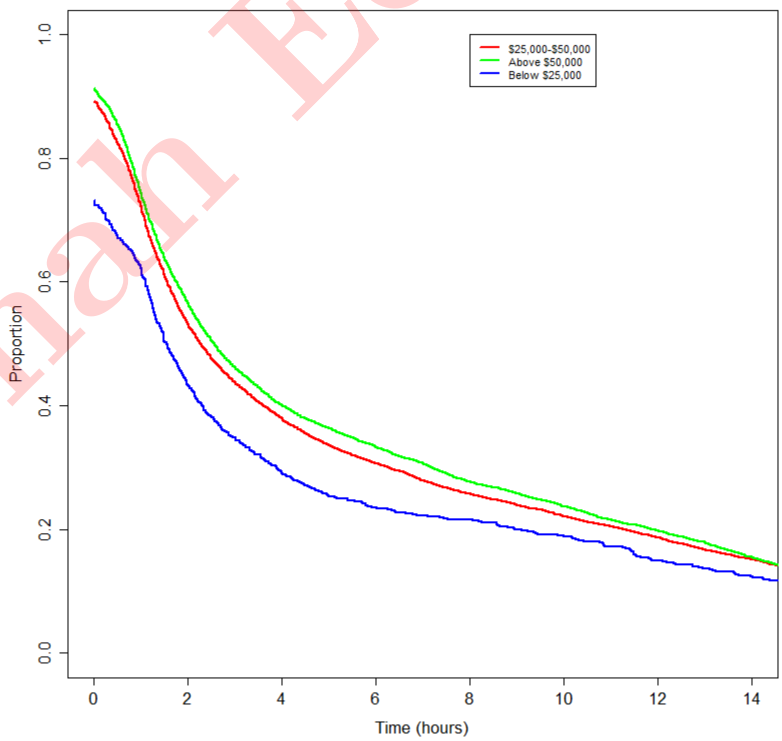

Figure 61: Kaplan-Meier curve for the Admit/transfer disposition decision to admission transition (State 4 - 5), separated by patient income.

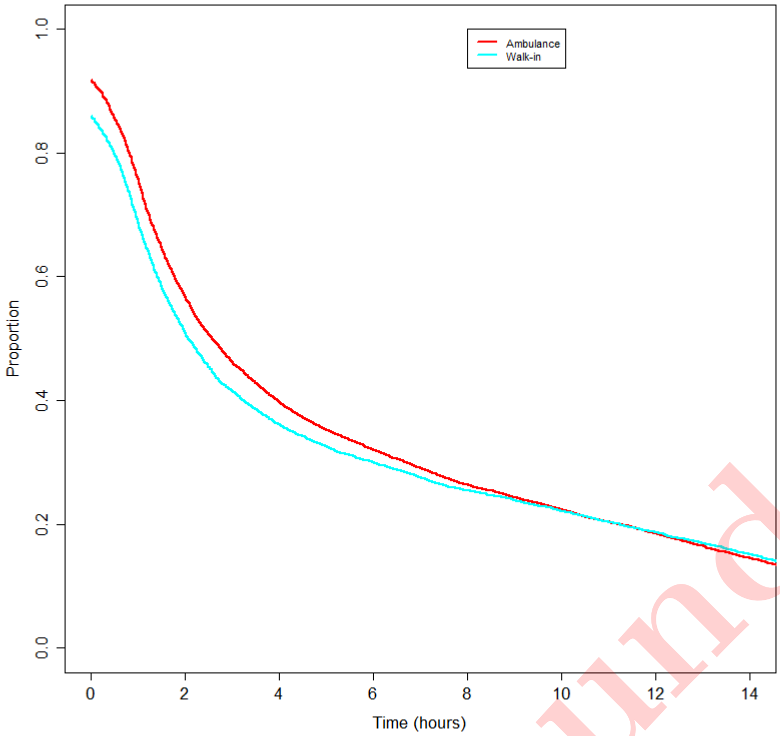

Figure 62: Kaplan-Meier curve for the Admit/transfer disposition decision to admission transition (State 4 - 5), separated by arrival type.

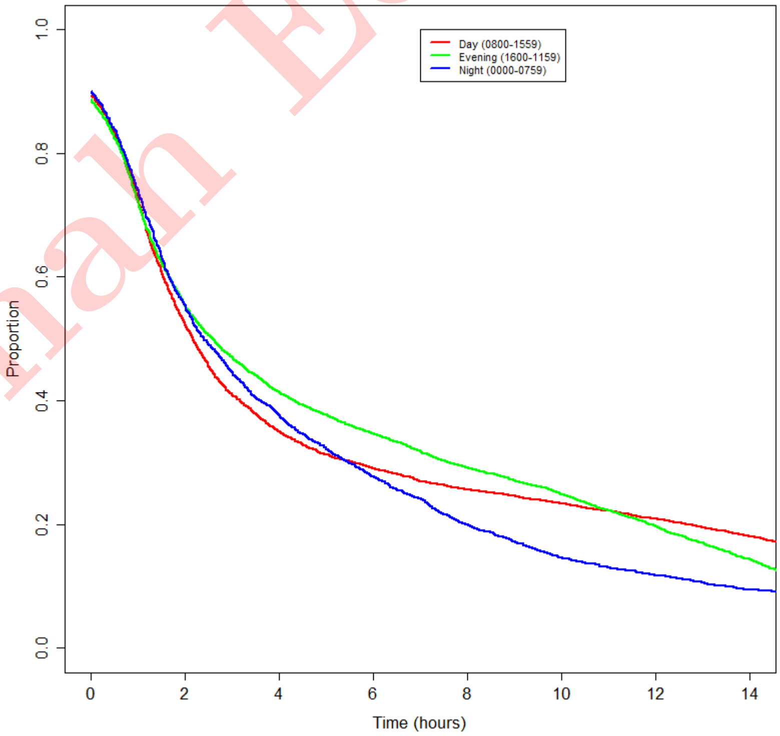

Figure 63: Kaplan-Meier curve for the Admit/transfer disposition decision to admission transition (State 4 - 5), separated by time of arrival.

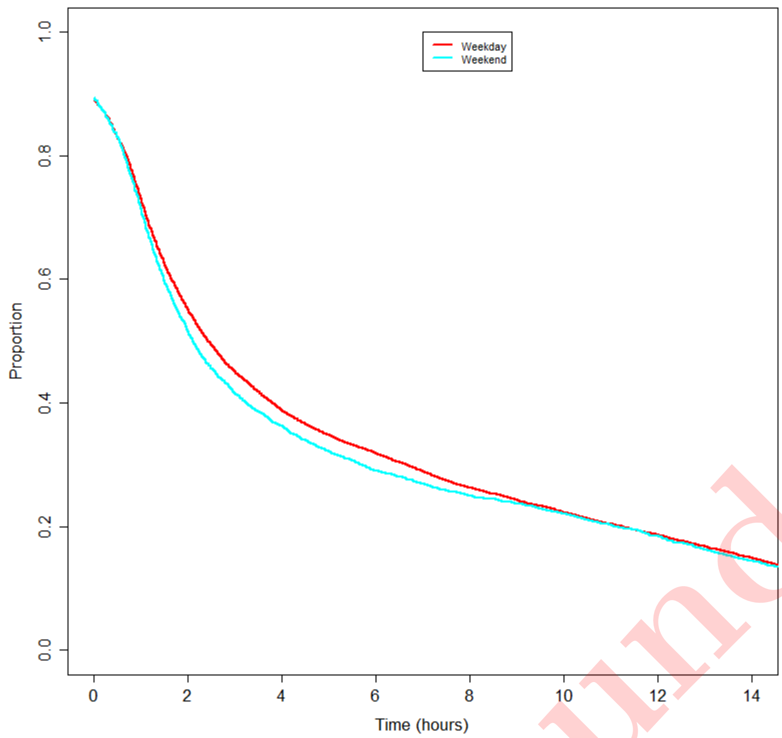

Figure 64: Kaplan-Meier curve for the Admit/transfer disposition decision to admission transition (State 4 - 5), separated by day of the week (weekend or weekday).

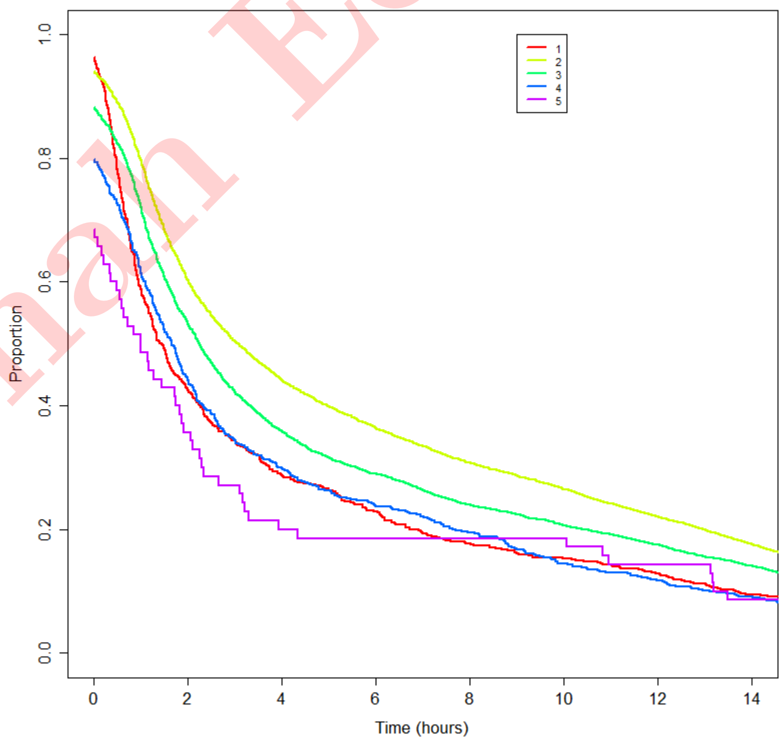

Figure 65: Kaplan-Meier curve for the Admit/transfer disposition decision to admission transition (State 4 - 5), separated by triage score (CTAS).

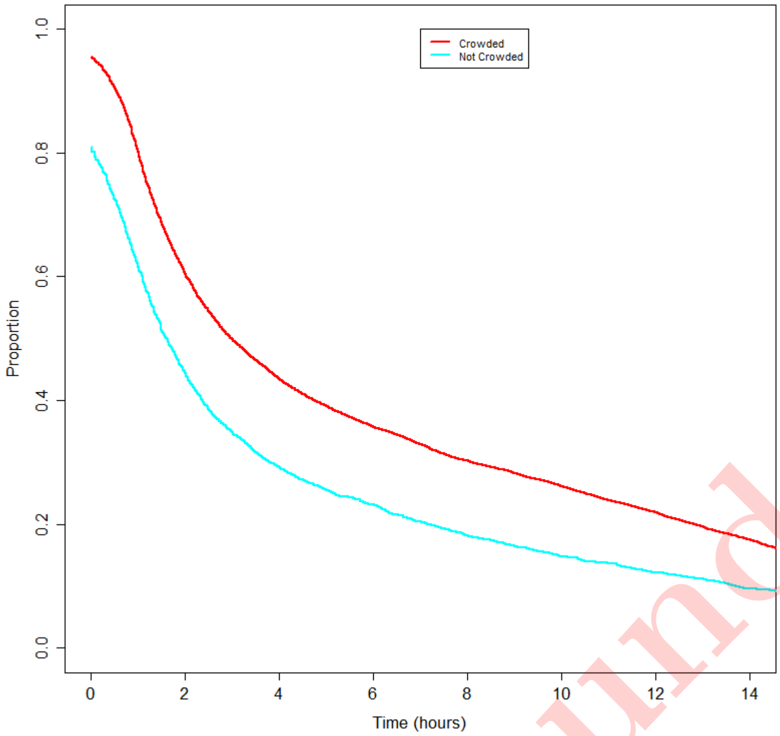

Figure 66: Kaplan-Meier curve for the Admit/transfer disposition decision to admission transition (State 4 - 5), separated by ED crowding status.

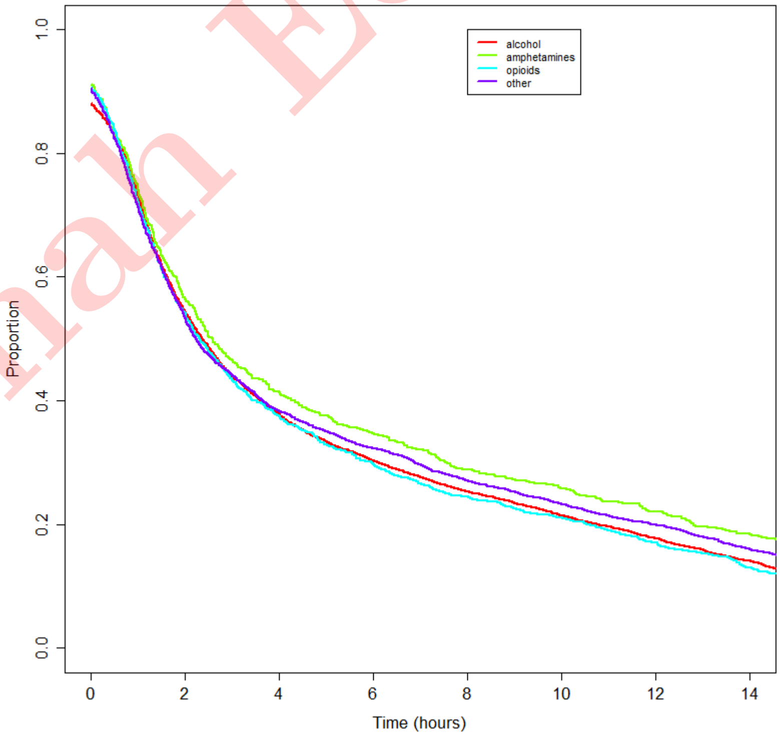

Figure 67: Kaplan-Meier curve for the Admit/transfer disposition decision to admission transition (State 4 - 5), separated by diagnostic code.

D.5 Admit/transfer disposition decision to transfer (State 4 - 6)

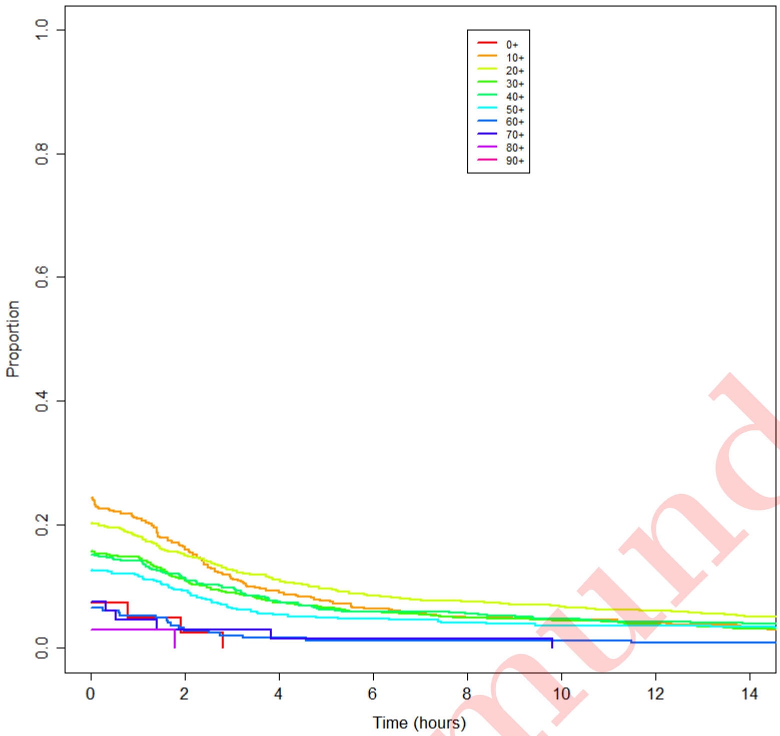

Figure 68: Kaplan-Meier curve for the Admit/transfer disposition decision to transfer transition (State 4 - 6), separated by age.

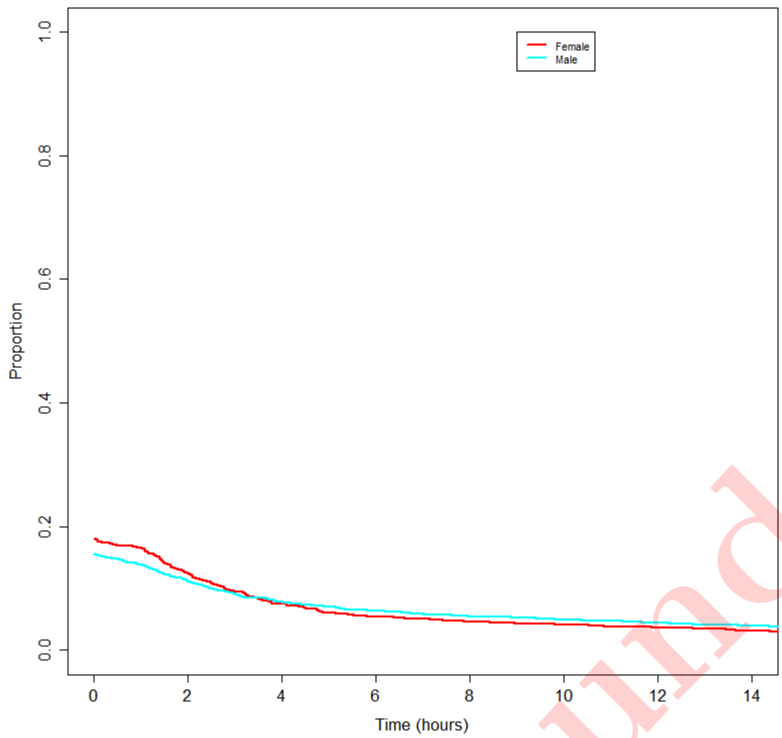

Figure 69: Kaplan-Meier curve for the Admit/transfer disposition decision to transfer transition (State 4 - 6), separated by gender.

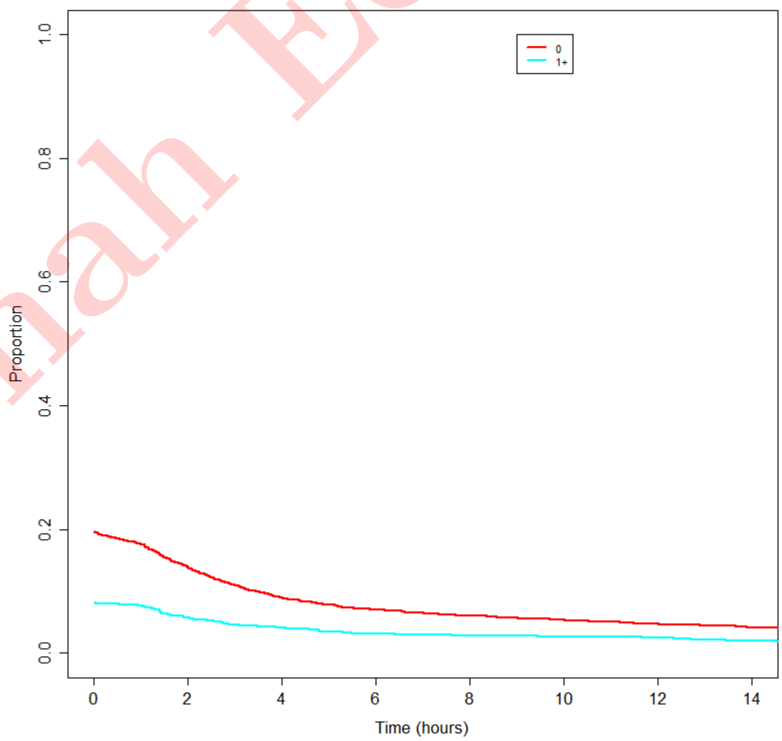

Figure 70: Kaplan-Meier curve for the Admit/transfer disposition decision to transfer transition (State 4 - 6), separated by Charlson index score.

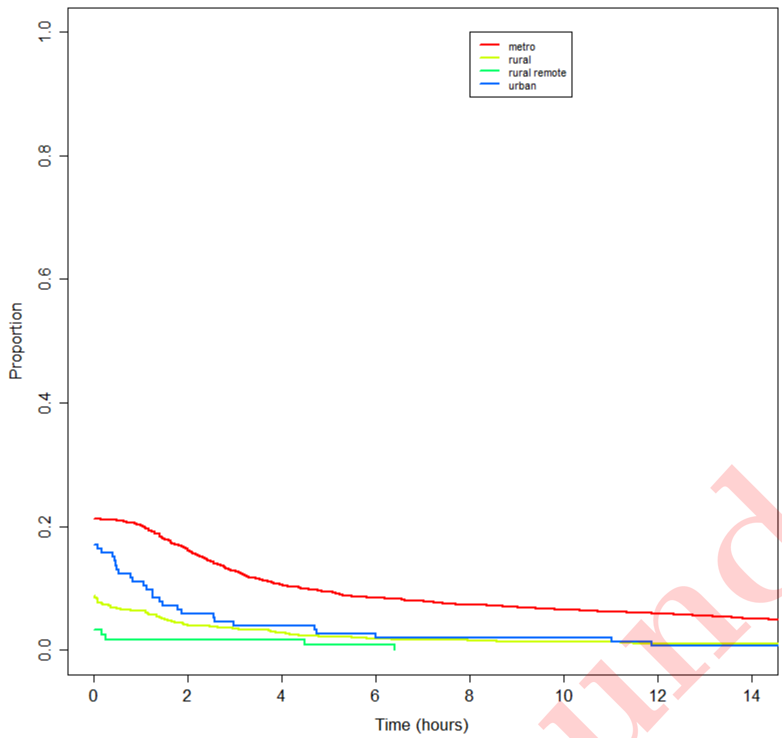

Figure 71: Kaplan-Meier curve for the Admit/transfer disposition decision to transfer transition (State 4 - 6), separated by patient municipality.

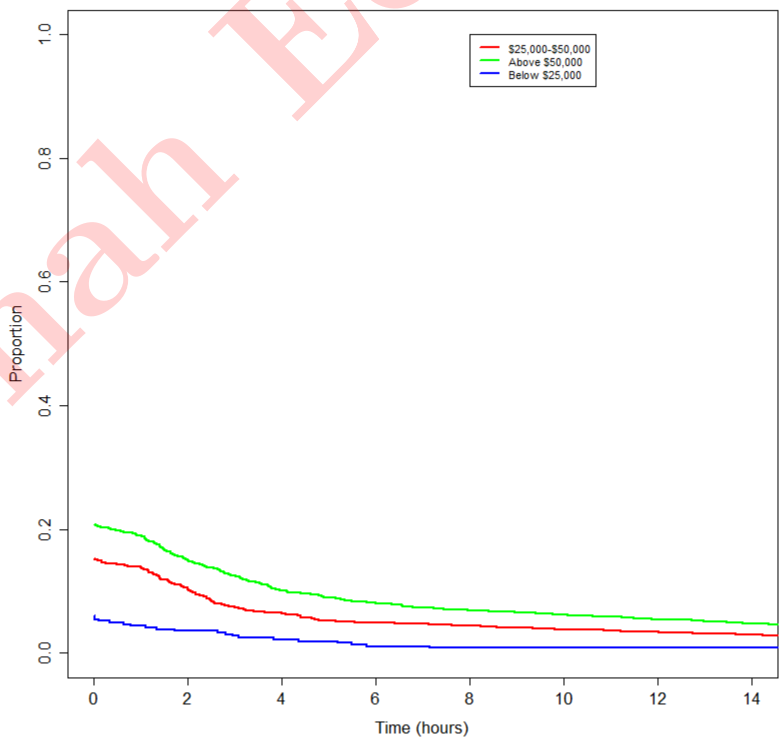

Figure 72: Kaplan-Meier curve for the Admit/transfer disposition decision to transfer transition (State 4 - 6), separated by patient income.

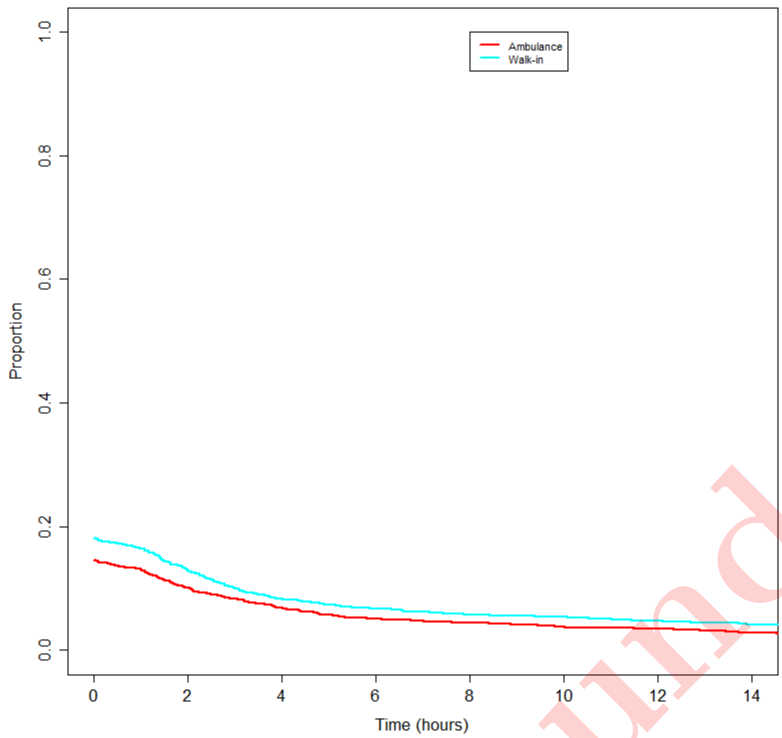

Figure 73: Kaplan-Meier curve for the Admit/transfer disposition decision to transfer transition (State 4 - 6), separated by arrival type.

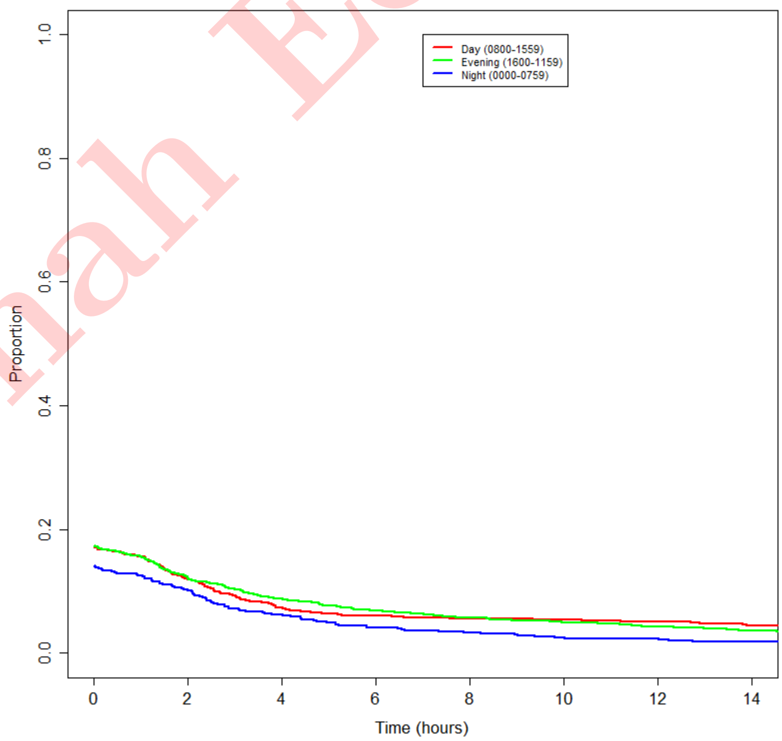

Figure 74: Kaplan-Meier curve for the Admit/transfer disposition decision to transfer transition (State 4 - 6), separated by time of arrival.

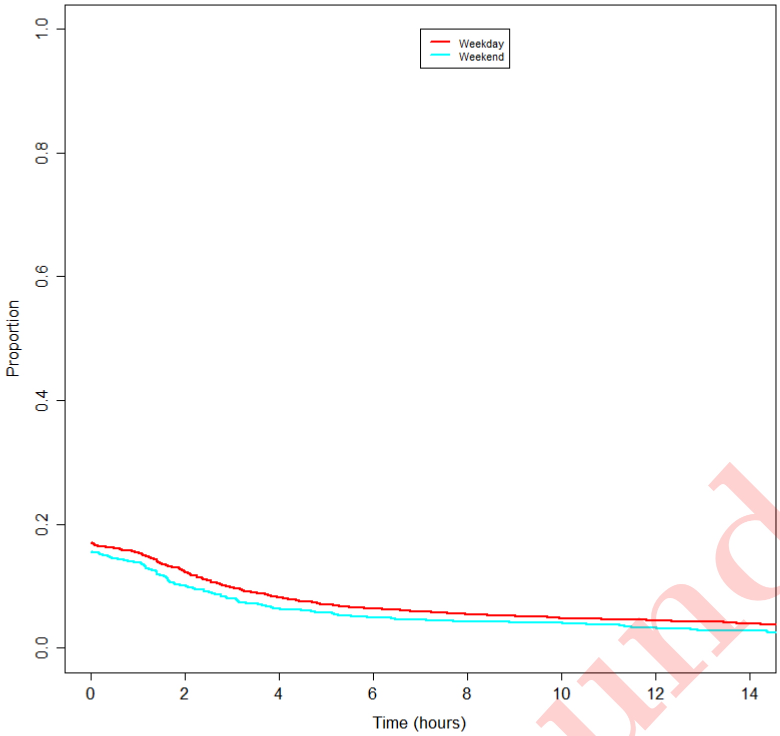

Figure 75: Kaplan-Meier curve for the Admit/transfer disposition decision to transfer transition (State 4 - 6), separated by day of the week (weekend or weekday).

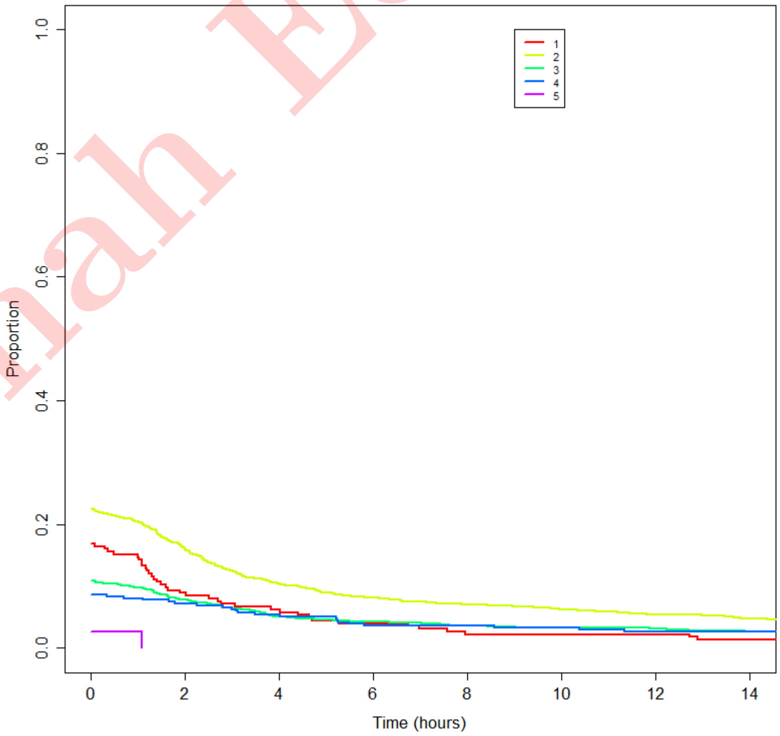

Figure 76: Kaplan-Meier curve for the Admit/transfer disposition decision to transfer transition (State 4 - 6), separated by triage score (CTAS).

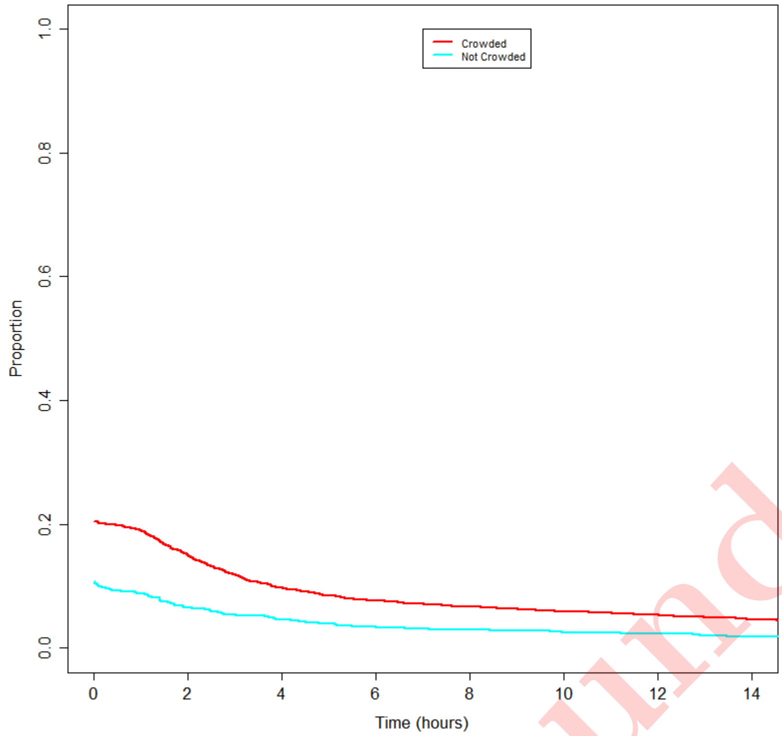

Figure 77: Kaplan-Meier curve for the Admit/transfer disposition decision to transfer transition (State 4 - 6), separated by ED crowding status.

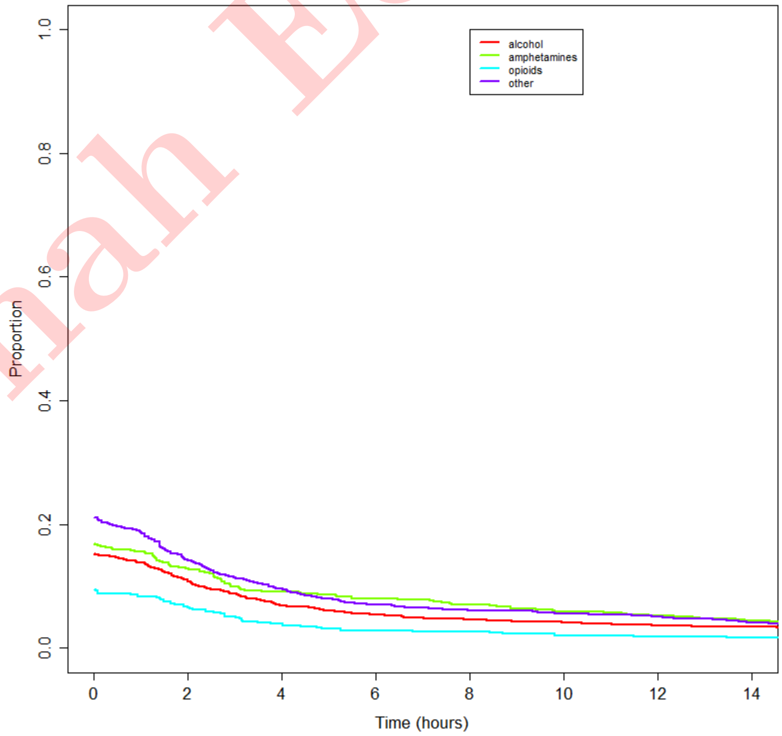

Figure 78: Kaplan-Meier curve for the Admit/transfer disposition decision to transfer transition (State 4 - 6), separated by diagnostic code.

D.6 PIA to LAMA (State 2 - 7)

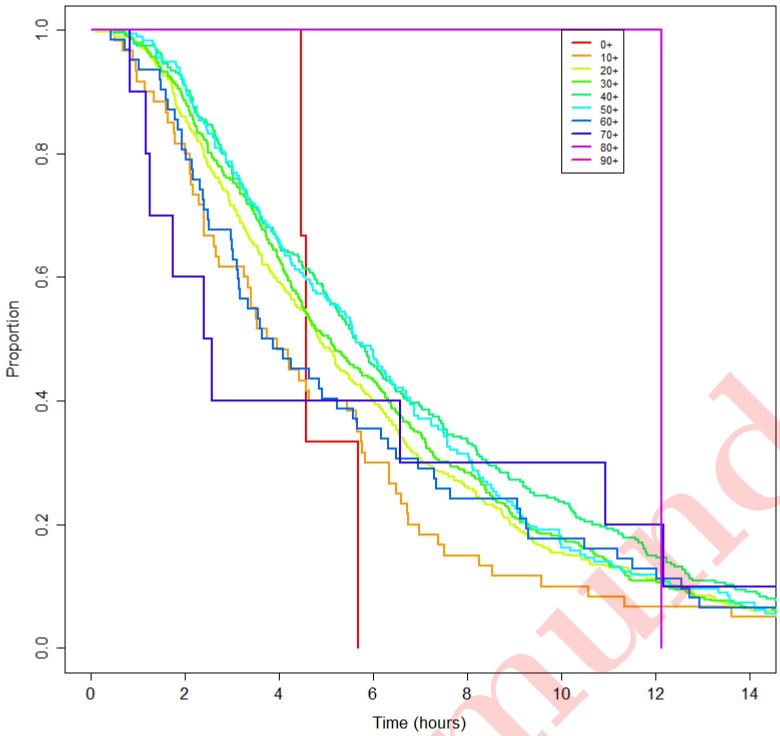

Figure 79: Kaplan-Meier curve for the PIA to LAMA transition (State 2 - 7), separated by age.

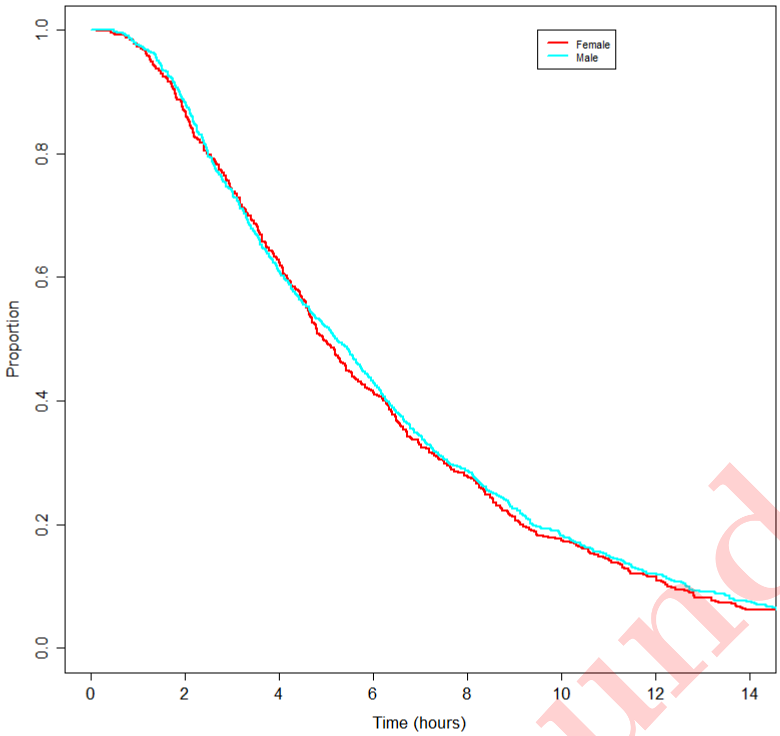

Figure 80: Kaplan-Meier curve for the PIA to LAMA transition (State 2 - 7), separated by gender.

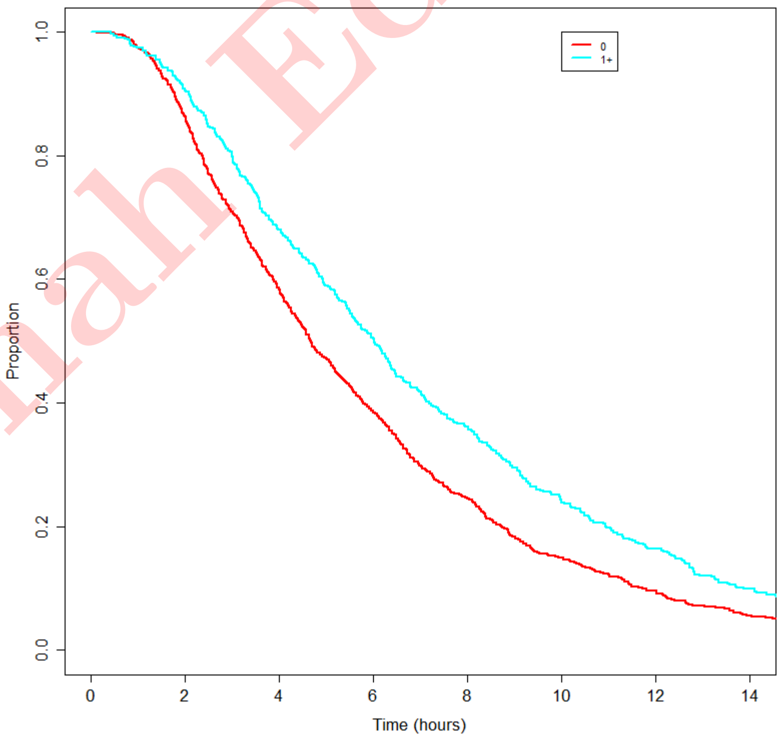

Figure 81: Kaplan-Meier curve for the PIA to LAMA transition (State 2 - 7), separated by Charlson index score.

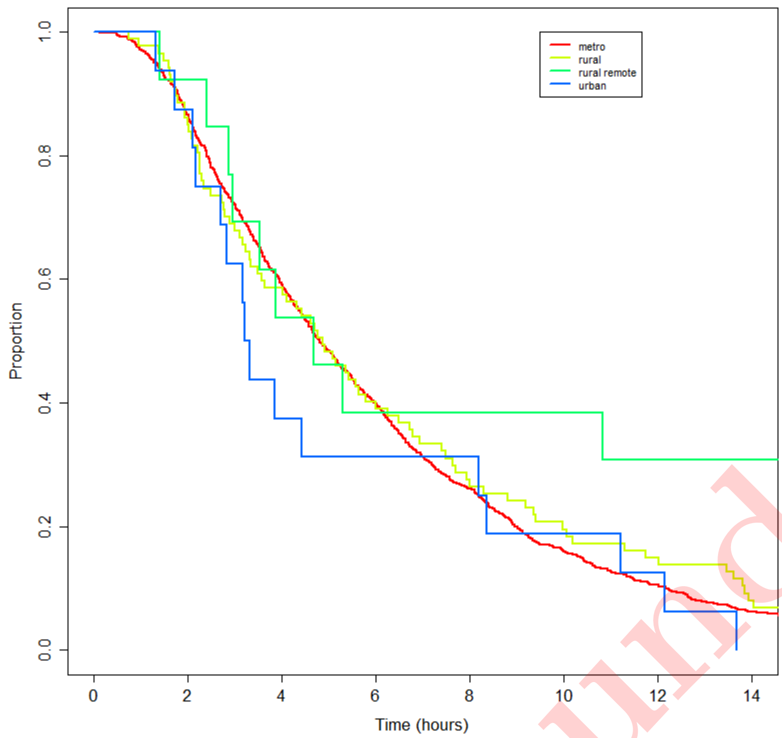

Figure 82: Kaplan-Meier curve for the PIA to LAMA transition (State 2 - 7), separated by patient municipality.

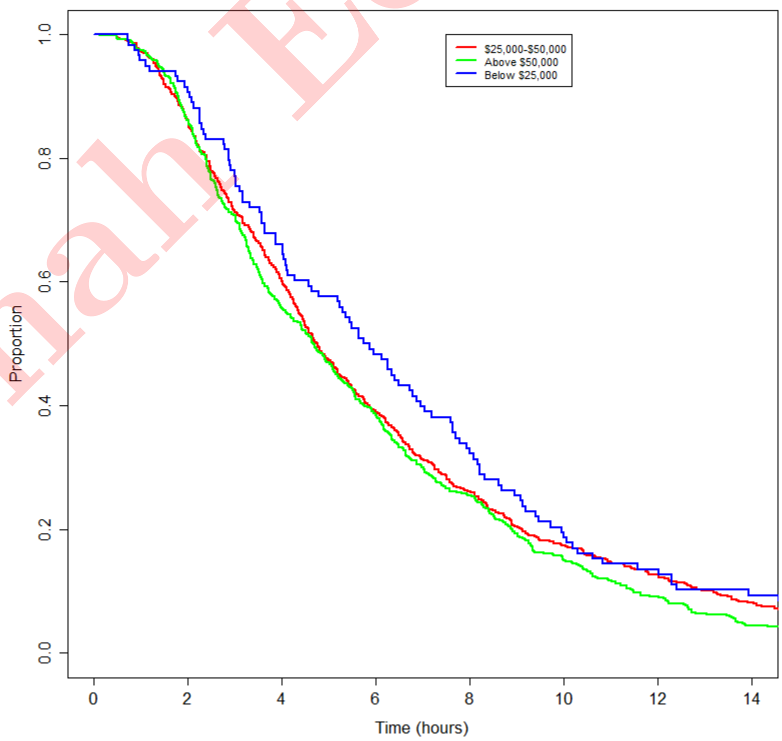

Figure 83: Kaplan-Meier curve for the PIA to LAMA transition (State 2 - 7), separated by patient income.

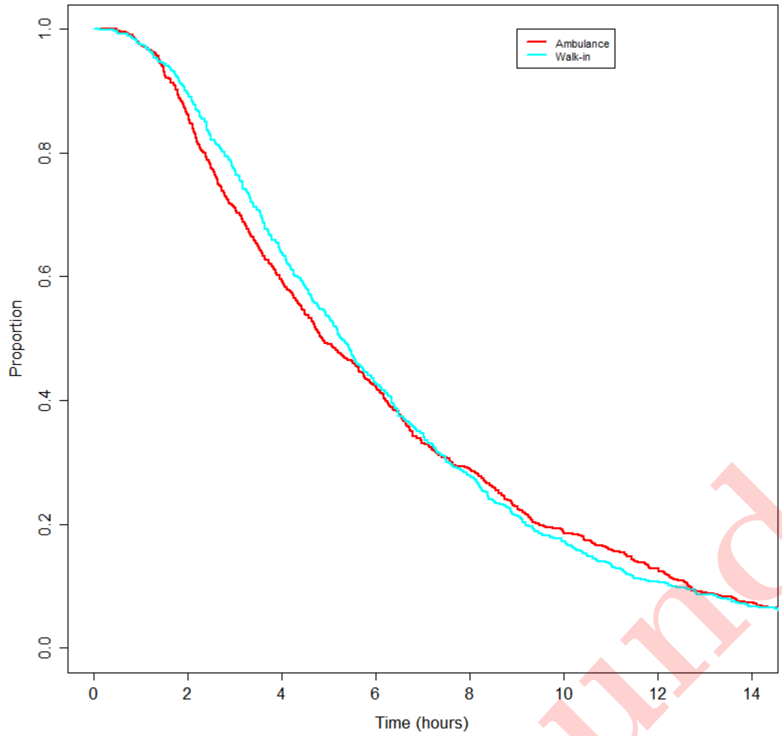

Figure 84: Kaplan-Meier curve for the PIA to LAMA transition (State 2 - 7), separated by arrival type.

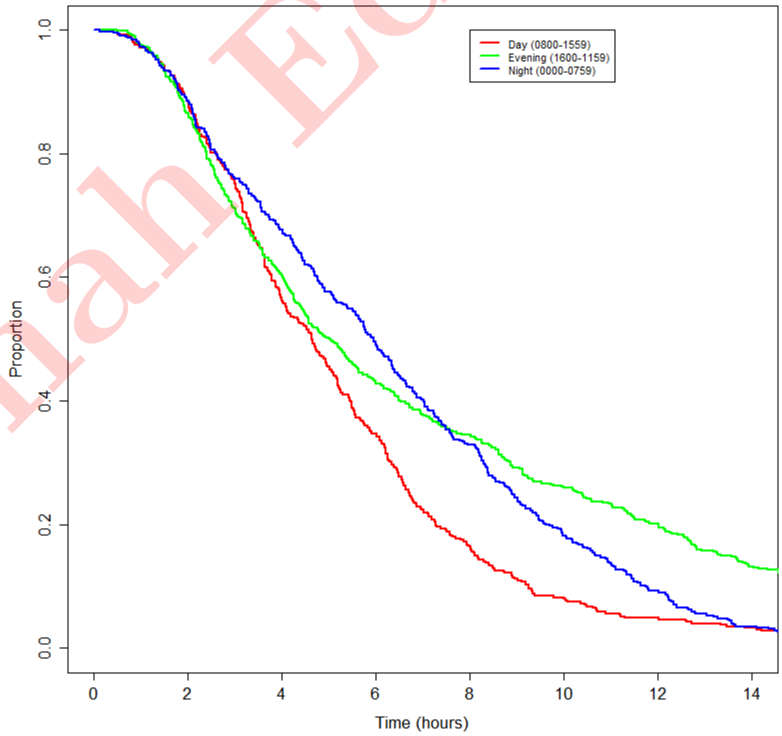

Figure 85: Kaplan-Meier curve for the PIA to LAMA transition (State 2 - 7), separated by time of arrival.

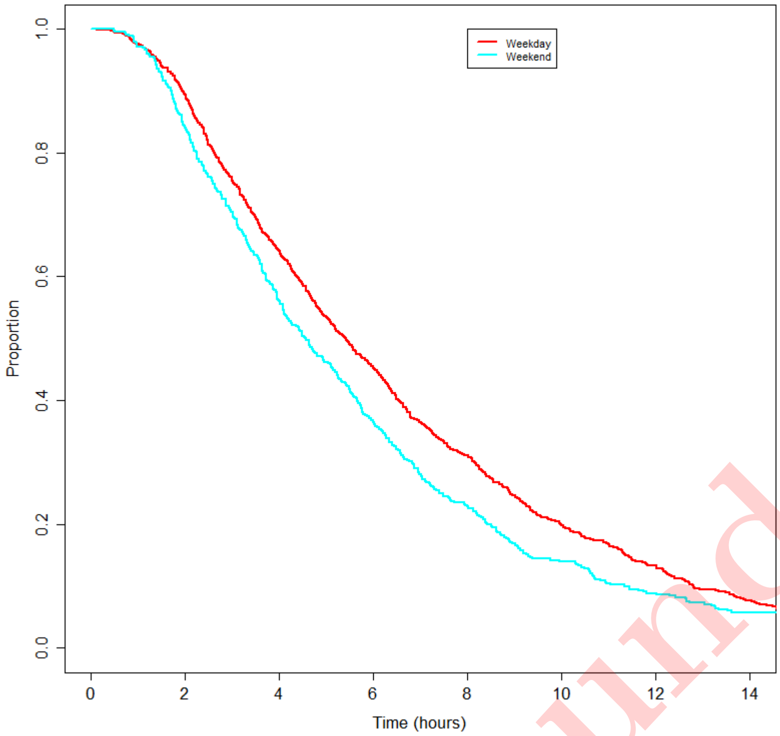

Figure 86: Kaplan-Meier curve for the PIA to LAMA transition (State 2 - 7), separated by day of the week (weekend or weekday).

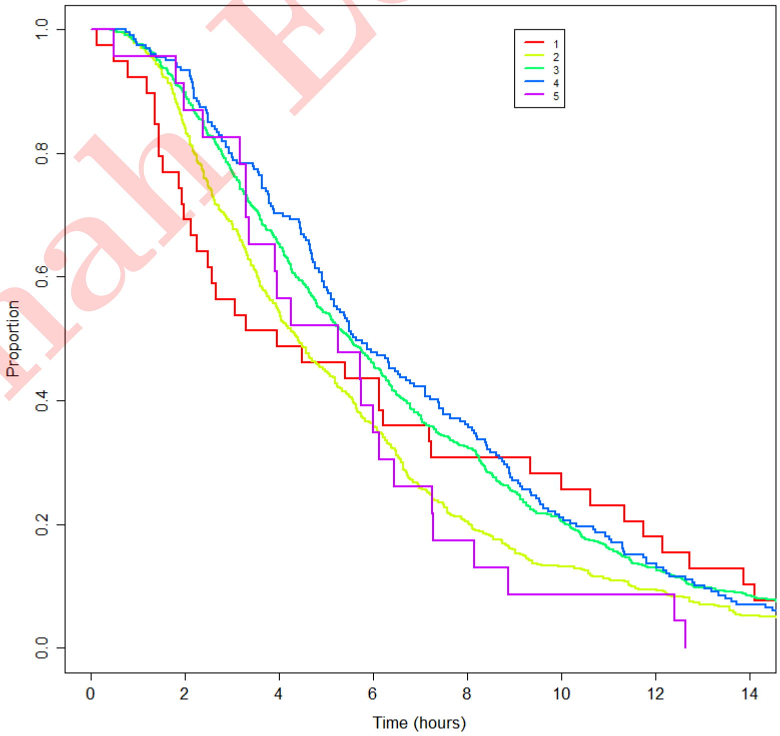

Figure 87: Kaplan-Meier curve for the PIA to LAMA transition (State 2 - 7), separated by triage score (CTAS).

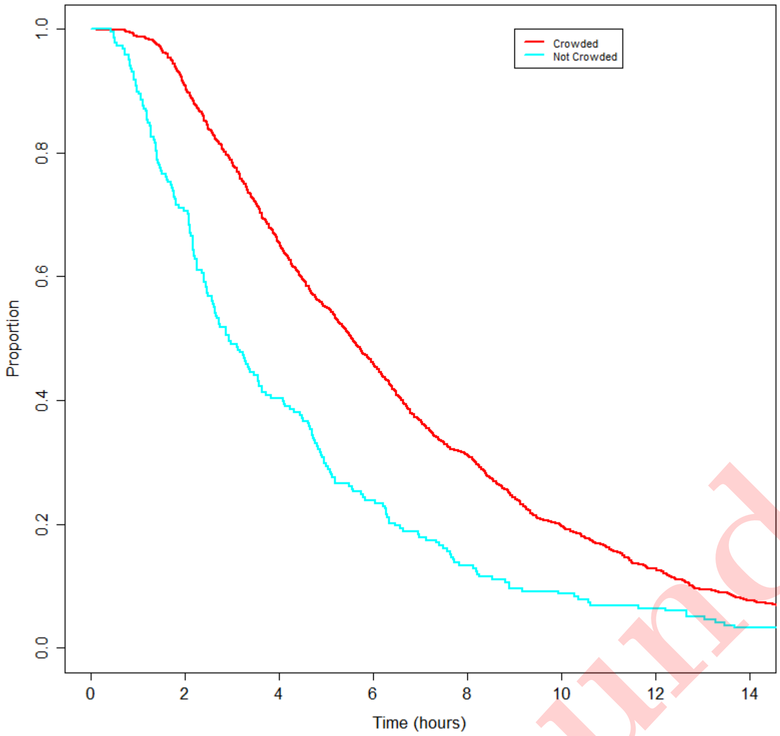

Figure 88: Kaplan-Meier curve for the PIA to LAMA transition (State 2 - 7), separated by ED crowding status.

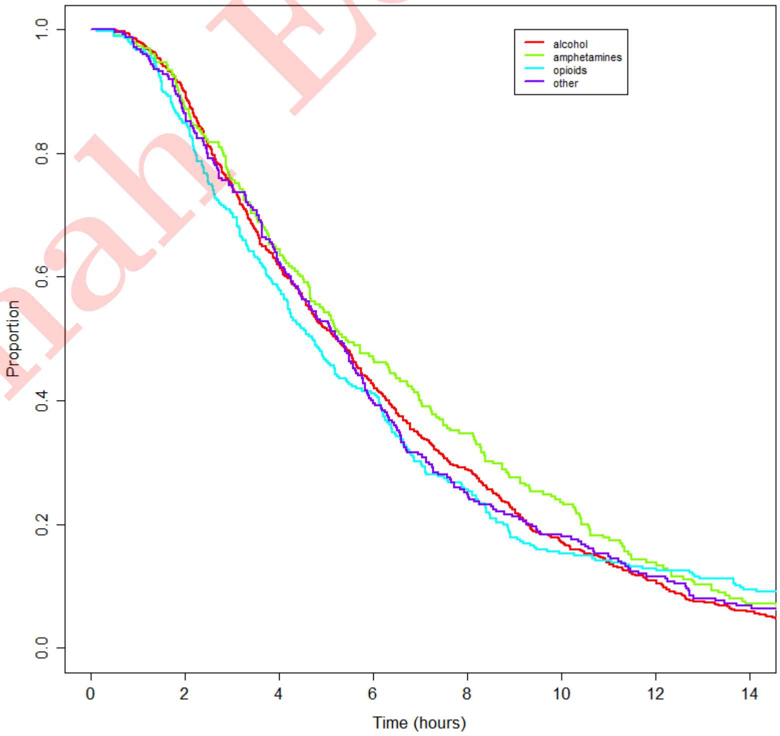

Figure 89: Kaplan-Meier curve for the PIA to LAMA transition (State 2 - 7), separated by diagnostic code.

E State Tables by Covariate

The following tables are arranged so that the levels of each covariate appear below a bolded heading of each covariate. These tables are formatted so that the starting states are on the y-axis along the side, and the receiving states are on the x-axis along the top.

These tables may appear unfinished, as they are a direct output from the `xtable` package in R.

"URBANreduced"

"metro"

	1	2	3	4	5	6	7
1	0	37905	0	0	0	0	0
2	0	0	26683	10035	0	0	1116
4	0	0	0	0	7625	2692	0

"rural"

	1	2	3	4	5	6	7
1	0	11172	0	0	0	0	0
2	0	0	7874	2808	0	0	89
4	0	0	0	0	2564	1017	0

"rural remote"

	1	2	3	4	5	6	7
1	0	1487	0	0	0	0	0
2	0	0	1000	397	0	0	13
4	0	0	0	0	494	120	0

"urban"

	1	2	3	4	5	6	7
1	0	6886	0	0	0	0	0
2	0	0	4909	1735	0	0	16
4	0	0	0	0	1627	153	0

"Charlson"

"0"

	1	2	3	4	5	6	7
1	0	45080	0	0	0	0	0
2	0	0	32981	10594	0	0	949
4	0	0	0	0	8394	3112	0

"1+"

	1	2	3	4	5	6	7
1	0	16085	0	0	0	0	0
2	0	0	10208	5169	0	0	468
4	0	0	0	0	4512	1092	0

"GENDER"

"M"

	1	2	3	4	5	6	7
1	0	37308	0	0	0	0	0
2	0	0	26303	9591	0	0	903
4	0	0	0	0	7810	2499	0

"F"

	1	2	3	4	5	6	7
1	0	23851	0	0	0	0	0
2	0	0	16885	6168	0	0	514
4	0	0	0	0	5092	1705	0

"ADMITBYAMB"

"None"

	1	2	3	4	5	6	7
1	0	31308	0	0	0	0	0
2	0	0	22959	7272	0	0	675
4	0	0	0	0	5697	2313	0

"Ground"

	1	2	3	4	5	6	7
1	0	29816	0	0	0	0	0
2	0	0	20210	8473	0	0	741
4	0	0	0	0	7196	1882	0

"incomecategory"

"Above $50,000"

	1	2	3	4	5	6	7
1	0	26797	0	0	0	0	0
2	0	0	18684	7275	0	0	553
4	0	0	0	0	5805	2098	0

"$25,000 to $50,000"

	1	2	3	4	5	6	7
1	0	25597	0	0	0	0	0
2	0	0	18096	6594	0	0	561
4	0	0	0	0	5629	1507	0

"Below $25,000"

	1	2	3	4	5	6	7
1	0	5056	0	0	0	0	0
2	0	0	3686	1106	0	0	120
4	0	0	0	0	876	377	0

"TRIAGECODE"

"1"

	1	2	3	4	5	6	7
1	0	2077	0	0	0	0	0
2	0	0	1139	885	0	0	41
4	0	0	0	0	759	243	0

"2"

	1	2	3	4	5	6	7
1	0	23550	0	0	0	0	0
2	0	0	15184	7652	0	0	506
4	0	0	0	0	6222	2065	0

"3"

	1	2	3	4	5	6	7
1	0	25840	0	0	0	0	0
2	0	0	19071	5733	0	0	648
4	0	0	0	0	4733	1461	0

"4"

	1	2	3	4	5	6	7
1	0	8080	0	0	0	0	0
2	0	0	6549	1183	0	0	199
4	0	0	0	0	890	354	0

"5"

	1	2	3	4	5	6	7
1	0	1153	0	0	0	0	0
2	0	0	987	126	0	0	23
4	0	0	0	0	80	41	0

"DXreduced"

"alcohol"

	1	2	3	4	5	6	7
1	0	30095	0	0	0	0	0
2	0	0	21063	7935	0	0	635
4	0	0	0	0	6763	1769	0

"meth"

	1	2	3	4	5	6	7
1	0	7340	0	0	0	0	0
2	0	0	5367	1667	0	0	229
4	0	0	0	0	1152	647	0

"opioids"

	1	2	3	4	5	6	7
1	0	8425	0	0	0	0	0
2	0	0	6198	1843	0	0	299
4	0	0	0	0	1434	508	0

"other"

	1	2	3	4	5	6	7
1	0	15305	0	0	0	0	0
2	0	0	10561	4318	0	0	254
4	0	0	0	0	3557	1280	0

"shift"

"Day (0800-1559)"

	1	2	3	4	5	6	7
1	0	19453	0	0	0	0	0
2	0	0	12955	5804	0	0	435
4	0	0	0	0	4939	1463	0

"Evening (1600-1159)"

	1	2	3	4	5	6	7
1	0	25627	0	0	0	0	0
2	0	0	18083	6693	0	0	522
4	0	0	0	0	5332	1856	0

"Night (0000-0759)"

	1	2	3	4	5	6	7
1	0	16085	0	0	0	0	0
2	0	0	12151	3266	0	0	460
4	0	0	0	0	2635	885	0

"weektime"

"Weekday"

	1	2	3	4	5	6	7
1	0	42241	0	0	0	0	0
2	0	0	29316	11409	0	0	958
4	0	0	0	0	9415	3008	0

"Weekend"

	1	2	3	4	5	6	7
1	0	18924	0	0	0	0	0
2	0	0	13873	4354	0	0	459
4	0	0	0	0	3491	1196	0

"piatime"

"Not Crowded"

	1	2	3	4	5	6	7
1	0	17019	0	0	0	0	0
2	0	0	12354	3968	0	0	222
4	0	0	0	0	2880	1094	0

"Crowded"

	1	2	3	4	5	6	7
1	0	44136	0	0	0	0	0
2	0	0	30828	11792	0	0	1195
4	0	0	0	0	9363	2813	0