Application of Data Science to Paramedic Data

A thesis submitted to the Committee on Graduate Studies

in partial fulfillment of the requirements for the degree of Master of Science

in the Faculty of Arts and Science

TRENT UNIVERSITY

Peterborough, Ontario, Canada

Applied Modelling and Quantitative Methods M.Sc. Graduate Program

May 2022

Abstract

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J. Chris Smith

Paramedic data has significant potential for research. Paramedics see many patients every year and collect a wide variety of crucial data at each encounter. This data is rarely used for good reason: it's messy and hard to work with. But like the underdog character in a classic movie, with a little bit of work and a lot of understanding, paramedic data has significant potential to change the world of medical research. Paramedics throughout the world are involved in research every day, but most of this research uses purpose-built data structures and never takes advantage of the existing data that paramedics create as part of their everyday work. Through a project-based approach grounded in developing a better understanding of the opioid crisis, this thesis will examine the quantity and structure of the existing paramedic data, the complexities of its current design, the steps necessary to access it, and the processes necessary to clean existing data to a point where it can be easily modelled. Once we have our dataset, we will explore the challenges of choosing key metrics by examining the effectiveness of metrics currently employed to monitor the opioid crisis and the influences public health programs and changing policies have had on these metrics. Next, we will explore the temporal distributions of opioid and other

intoxicant use with an eye to providing data to support public health in their harm reduction efforts. And lastly, we will look at the effect of fixed- and floating-point temporal influences on intoxicant-related calls with an eye to how these temporal points can affect call volumes. By using this exploration of the opioid crisis, this thesis will show that with a more thorough understanding of what paramedic data is, what data points are available, and the processes needed to transform it, paramedic data has the potential to greatly expand the limits of health care data science into a more precise and more all-encompassing discipline.

Acknowledgements

I would like to thank the three service that contributed data to this thesis. Without the support and contributions of Peterborough County/City Paramedics, Kawartha Lakes Paramedic Service and Haliburton Paramedic Service, this thesis would not have been possible. This specifically includes Chief of PCCP and KLPS Randy Mellow and Deputy Chief Don Oettinger of PCCP for their support and letting me bug them with all my random ideas, some of which have actually worked out. I would also like to thank the McNally Project and all its members for being a great sounding board and source of ideas and inspiration through out this project.

I would like to thank my supervisor Dr. Wesley Burr for his ongoing support and for taking a chance on the random guy in a uniform who showed up in his office one day looking for help with some stats.

And lastly (but certainly not least), I dedicate this work to my amazing wife Karen and my daughters Allison and Rebecca. While it has been a busy and interesting 2.5 years, your support and love, along with randomly delivered snacks and day trips out of the house during a worldwide pandemic, have made all this “fancy math” possible.

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List of Abbreviations and Symbols

ACR: Ambulance Call Report

CCB: Canadian Child Benefit

ED: Emergency Department

ePCR: Electronic Patient Care Report

OW: Ontario Works

ODSP: Ontario Disability Support Program

OW/ODPS: Ontario Works/Ontario Disability Support Program

PCR: Patient Care Report

TLA: Three Letter Acronym

Nomenclature and Glossary

Ambulance Call Report: the patient care record used by paramedics in Ontario.

Bystander Naloxone: Within the confines of this thesis, this term will refer to patients being given naloxone by a member of the public prior to paramedic arrival. This term specifically excludes on-duty paramedics or on-duty members of the police or fire service. However, it does not make any comment on the relationship between the patient and the bystander, except where explicitly stated.

Canadian Child Benefit: a tax-free Canadian federal government payment to support eligible families with the costs of raising children.

Computer Aided Dispatch: Ambulance dispatches use a complicated system of integrated computers to improve performance and assist communication officers with prioritizing calls and tracking paramedic resources.

Car Count: In general, this refers to the number of vehicles a paramedic service has in service at a given point in time. The count will vary depending on time of day, available staffing and different types of upstaffing. The count will also vary depending on the type of question being asked, as certain specialized units may not be relevant to certain types of analysis.

Day-car: A ambulance which is only staffed during the day. Typically, a day-car is staffed for a 8-, 10-, or 12-hour day shift and the vehicle sits idle over night. These are used to accommodate for higher call volumes during the daytime hours.

Electronic Patient Care Report: an electronic version of a patient care report.

Ontario Disability Support Program: the Ontario provincial government social assistance program for those residents in financial need who are unemployed or underemployed due to a disability (as defined by the ODSP Act of 1997), or those who meet the definition of a "Prescribed Case" as defined by the Ontario Ministry of Children, Community and Social Services [1].

Ontario Works: Ontario provincial government social assistance program for those who are in financial need and unemployed [1].

Paramedic Naloxone: Within the confines of this thesis, this term will refer to patients being given naloxone by an on-duty paramedic, which is recorded on the patient care record for that case as being given by a paramedic. It does not make a distinction between levels of care or position of the paramedic within the paramedic service (i.e., supervisors, front-line, community paramedic, special event medics, etc.).

Patient Care Report: Patient Care Report is a generic term for the form use to document the medical treatment that a patient receives.

Upstaff: The addition of an additional staffed ambulance beyond the normal complement. Upstaffing can be done as a pre-scheduled event to account for predicted increased call volumes or special events or as an emergent response to depletion of service resource.

Chapter 1

Introduction

The world of paramedicine is a relative newcomer to the world of medicine. While today's highly skilled paramedics can link their ancestry back to various points in history, the modern concept of the highly skilled and knowledgeable (non-physician) civilian paramedic bringing hospital-level care to patients goes back only to the 1970s and the establishment of the first paramedic units created under the Wentworth-Townsend Paramedic Act in California [2]. Compared to other areas of medicine that go back hundreds of years, this is but a blip in time (e.g., Oxford University has been teaching some form of medicine since 1546
[3]). As such, the idea of pre-hospital science or paramedicine is still developing and this process has been slow. While some countries have transitioned to a degree entry to practice (i.e., UK and Australia) most Canadian and American paramedics do not require degrees to practice. This limited academic experience is not restricted just to those practicing but extends into the world of research. The website

ParamedicPHD.com allows Ph.D and other Doctoral degree holders to register their doctoral studies related to paramedicine. As of October 2021, only 212 paramedic Ph.D.s had been registered worldwide, with only 4 being related to data science[1].

This limited formal academic education has led to slow progress in the development of paramedic science, including specifically the application of data science to paramedic-related data. While the literature for the application of data science in paramedicine is starting to appear, it has primarily focused on areas where data is best suited for modelling. Recent research has focused on the prediction of call volumes, optimal location for bases, and ideal scheduling patterns for operational efficiency using machine learning. However, these areas use only the most basic features of paramedic data (e.g., call location and date/time), which are not usually derived from paramedic data at all, but from dispatch data. While dispatch data is often cleaner, thanks to computer aided dispatch programs, it does not encompass the full potential of what paramedic data could tell us about patient populations and operational realities.

With a more thorough understanding of what paramedic data is, what data points are available, and the process needed to transform it, paramedic data has the potential to greatly expand the limits of health care data science into a more precise and more all-encompassing discipline.

[1] I acknowledge that non-paramedics can do paramedic data science, but as will be discussed later, extensive domain knowledge is essential for success.

1.1 Available data:

Perhaps one of the most promising aspects of paramedic data with regards to data science is that the quantity of data available from paramedic records is astounding. The average Canadian paramedic service sees an annual patient population equivalent to 10-15% of the population of its coverage area[2]. If we assume this holds true for the entire country (population 38 million [4]) then each year Canadian paramedics encounter and document 3.8-5.7 million calls for service. For each call for service, a large number of distinct data points are required to be documented.

While each province is unique in the requirements of its reporting system, this thesis deals primarily with Ontario paramedic data so we will focus on the Ontario requirements here. For the most basic of calls, where a paramedic arrives on scene but finds no patient, a minimum of ~ 40 separate data points are required. This increases to >150 separate data points if a patient is transported with no significant patient care and increases further to over 500 separate data points for complex or long-duration calls. This means that upwards of 380 million unique data points are generated each year, the vast majority of which are entirely digital.

[2]This number was determined by examining the annual reports of multiple paramedic services and comparing their annual patient counts to the published populations of their coverage area at the time of the report. The paramedic services examined were the City of Toronto, Haliburton County, the City of Kawartha Lakes, Peterborough County, and the County of Simcoe, as well as PEI's Island EMS and British Columbia Ambulance Service.

1.2 Paramedic data is a mess

1.2.1 Missing data

While Paramedic data presents an amazing opportunity it also has significant issues. One major issue that is commonly reported is the amount of missing data. One of the most basic measures of data quality is its completeness [5] as greater than 10% missing data can compromise statistical analysis [6] and without quality data, it is difficult to do effective research [5]. While data missingness is commonly reported, it is rarely examined. In one systematic review of traumatic injuries, Mulholland *et al.* [7] found that 5 of the 9 studies reported significant levels of missing data but only 2 examined the rate of missingness. One of these studies found that data missing rates did not significantly impact their study, while the other found significant differences in the rates of missing data between the study groups, biasing the results.

The rate at which data is missing is also not uniform across paramedicine. Data that is stored as a finite number of "codes" (categorical variables) was found to be the least missing type of data, while data that would be captured in a free-text style narrative was missing up to 60% of the time [8]. While many studies do report on the missingness of their data, no reviews of entire Patient Care Report (PCR) databases were found in the literature to quantify the level of missing data at the systemic level.

The most comprehensive review published to date examines the Michigan EMS Information System (MI-EMSIS) for 2010-2015 [9]. MI-EMSIS is the state component of the National EMS Information System, a national database of 430 data points administered by the National Highway Traffic Safety Administration. While the authors used only descriptive statistics, they found high levels of missingness in data, many over 30% across all 5 years. They also found "substantial variability" in levels of missingness across the various EMS agencies, Medical Control Authorities, and different software platforms. Differences between agencies and Medical Control Authorities were believed to be related to differing levels of quality assurance practice at the various agencies and authorities. Differences between software platforms were believed to be related to differences in data entry interfaces, different compliance options, and problems with data mapping between the various software and the state registry.

The only published comparison for Ontario data examined paper-based ambulance records from 1991 and found that 15% of relevant data was missing, but did not go any further in their analysis [10]. The current state of modern Canadian paramedic data, at least with regards to completeness, is unknown.

Over time, various systems and processes have been implemented in an effort to reduce data missingness. One example that was found to be very successful was the implementation of dedicated study coordinators/managers who monitor study data on a daily basis [11]. While this may be practical for single site, or even small multi-center prospective trials, it is not a practical approach for retrospective reviews or any study involving big data as the time involved in manual review for large quantities of data is prohibitive.

Another tool commonly employed is the introduction of compliance rules in charting software systems. These automated data compliance processes are systems within the charting software that review data and notify the paramedic if required data elements are missing or if data points do not conform to a required specification (e.g., times of call must be sequential in order and must not be in the future – you can not make patient contact before you arrive on scene – or Dates must be formatted as ####/##/##). While these compliance rules do encourage completeness, they can also encourage false entries in data to "bypass" compliance rules when the data is not available. While these false entries are usually obviously false[3] (e.g., postal code of "x0x 0x0" or Call Number of "1234567") this must be accounted for in the analysis. Required compliance rules can also introduce the concept of the "bare minimum effect" [9] which is where paramedics complete only those elements which are required and no more. This not only leads to poor documentation habits but also limits the amount of data that is available for analysis. While compliance rules are easily updated, the significant "gray area" of paramedicine makes creating compliance rules for all situations nearly impossible. As well, frequent, and rapid updates to compliance rules have been shown to lead to frustration and anger [12] in paramedics.

One consideration for missing data is that sometimes the data is not missing but never existed (e.g., homeless persons do not have addresses or postal codes). While most of these cases would be obvious when reviewing the record in its entirety, when data is abstracted in a data science approach, the nuances are lost. Most organizations specify a specific entry for use when data is not available, (Ontario specifies "CNO" - Could Not Obtain [13]) but these are not compliant with categorical or numeric fields and are not necessarily used consistently. Another common practice is to add a data entry that is appropriate under the circumstances related to why the data is not available but is not consistent with the expected data structure. One common example is to enter "no fixed" or "homeless" under address for a homeless person,

[3]Not all entries are obviously fake. One paramedic entered his own postal code for all patients for many years before it was discovered. When asked, his explanation was that he did not think anyone was going to use the postal code and it got past the compliance rule.

however, when you try to map "no fixed" with a programming system, it simply returns an error and considers the data missing. Again, while this would be obvious under manual review, it can be easily lost in big data scenarios.

Types of Missing Data

While there are many reasons why data might be missing, it is important to consider how we will deal with the missing data. Data can be considered missing in 3 different ways [6]:

- Missing Completely At Random
- Missing At Random
- Not Missing at Random

Missing Completely At Random happens in cases where it is not possible to distinguish those participants who have missing data from those who have complete data. In these cases, the impact of missing data should not significantly affect statistical analysis, as long as the proportion of data missing is not excessive. An example of this in paramedic data is a paramedic's ID number. If the ID number is missing it is most likely due to a typographical error or being forgotten and as such would be a random event.

Missing At Random cases are where those participants with complete data are distinguishable from those who have missing data, but the connection of which subjects' data are missing versus not missing data is relatable to other variables in the dataset [6]. Another way to think of it is that missing at random implies that the missing data is related to the subject, but not related to the area of interest for our analysis [14, p. 306]. An example of this in paramedic data would be date of birth. It is most commonly missing when the person is unable to provide their birthday due to being unconscious, or through a mental disability such as dementia. In these cases, the missing data is unlikely to affect analysis as the reason for the data being missing is already accounted for in other components of the data analysis (Altered level of consciousness scores or history of dementia).

Not Missing at Random happens when the missing data is directly related to the area of interests or the missing piece of data itself [14, p. 306]. In these cases, the missingness may be an important component of the analysis. An example of this would be a missing address in opioid overdose patients. Since a significant portion of this population experiences homelessness [15], a missing address is an important factor as it would be unknown if the address was not entered properly, the paramedic could not determine an address, or if the patient was truly homeless.

Unfortunately, there is no test to determine what type of missing data is present within a dataset. It must be determined by prior knowledge of the subject matter. For the most part, data examined here is assumed to be Missing Completely At Random or Missing At Random and cases with missing data are excluded from individual analysis, unless described otherwise.

1.2.2 Data structure in Ontario

In order to understand paramedic data, we must also discuss the system that creates it. Responsibility for the provision of ambulance services in Ontario was downloaded from a provincially run system to the upper-tier municipality in 2000. Since then, most ambulance services have been run by county/regional governments in southern Ontario or District Social Services Boards in the unincorporated areas of northern

Ontario. Each service is responsible for the collection and storage of its own Ambulance Call Reports (ACRs) which is what the Ontario Ministry of Health and Long-Term Care (more commonly refereed to as the Ministry of Health) call their PCRs. The Ministry of Health sets the minimum requirement of the ACR under the Ambulance Documentation Standard [16] and the Ambulance Call Report Completion Manual [13]. The ACR evolved from a paper report and today still exists as fully cross-compatible electronic and paper versions (paper is retained as a backup for computer failure and disaster situations, but all Ontario services are now required to use electronic reporting). In fact, any electronic version is required to have "equivalent prompts, codes and reference information available to paramedics to assist them in correctly inputting data" [16]. The current ePCR program used by most services in Ontario is a visual duplicate of the previous paper version with codes and data entry boxes updated to match the current version[4].

While the ACR itself is highly standardized, the standards and completion manuals allow a wide latitude for a paramedic's "style" in completing the ACR. For instance, the Ambulance Call Report Completion Manual produced by the Ministry of Health provides only high level instruction on completing the ACR and includes very few definitions for the various codes and data elements that are required [13]. As well, no separate data dictionary exists for the ACR meaning that each code or term used in the ACR can mean slightly different things to each paramedic. As an example, *procedure code 234: patient transported semi-sitting* is used by some paramedics to describe the time they put the patient on the stretcher and by others to describe the

[4]Note: PCR, ePCR and ACR are often used interchangeably, but they have subtle differences which are important. For the purposes of this thesis, I will use PCR when talking about patient care reports in general, ePCR will be used when talking specifically about electronic programs and electronic versions of forms, and ACR will be used when talking about the specifics of Ontario's Ambulance Call Report.

time when they start transport/depart scene. Even larger differences exist between services, which have developed their own way of using codes. As such it is important to have significant familiarity with the data and how it is used from a paramedic perspective in order to select the correct data points for any analysis. In many cases, multiple data points may be needed in a multi-level AND|OR type query to truly capture the wide variety of ways in which a given scenario could be documented.

The most commonly used electronic version of the ACR is the iMedic program from Interdev Technologies (Toronto, ON) and is the program used by all services contributing data to this thesis. This uniform data structure will reduce the possibility of cross-platform data mapping errors leading to missing data that was found by Abir *et al.* [9]. While the issue has been resolved for the purposes of this thesis, the issue of cross-platform data mapping remains a significant obstruction to inter-provincial and international paramedic research and will be discussed next.

1.2.3 Lack of a Data Dictionary

The lack of a proper data dictionary for paramedic data is also commonly reported as an obstacle to pre-hospital research [8]. While the National Highway Traffic Safety Authority committed to completing a full data dictionary for the NEMSIS project in 2008, studies have found that even after multiple updates, up to 29% of injury cases were miscoded or omitted altogether due to missing definitions in the updated NEMSIS data dictionary [8]. In Canada, the Paramedic Chiefs of Canada (PCC) have attempted multiple times to create a national paramedic data dictionary, however, they have never been successful. In 2012, PCC[5] was able to create a performance

[5]PCC was named "EMS Chiefs of Canada" prior to 2013.

measure data dictionary, however, it was limited to only certain aspects of key performance indicators and did not encompass many basic operational features (e.g., what does each province call the use of lights and sirens). Without this level of interprovincial (or even inter-service) data mapping, each research project must negotiate its own data map in order to conduct even basic multi-center research.

In their paper *Principles to Guide the Future of Paramedicine in Canada*, Taveras *et al.* [17], specifically listed inter-jurisdictional data sharing and the ability to easily link datasets as a key element in the future development of Canadian Paramedicine. While this thesis does not work with interprovincial data, integrating data from 3 services formed a similar framework for the creation of code and process to integrate separate datasets and then test for proper integration. Data cleaning is a major component of any data science project and paramedic data is no different. The code created during this project was specifically developed to be adaptable and easily reproducible as a guide for future multi-center projects.

1.3 What can paramedic data tell us?

Now that we have discussed the things that are wrong with paramedic data, let us switch gears and examine the potentials for paramedic data. Paramedics represent a unique crossroads between healthcare professionals and first responders. Depending on the region and level of care available, paramedics bring the critical care knowledge of a big city ED directly to the rural/remote trauma scene or the bedside of an ill patient. This is unique in health care in that paramedics are one of the only health care professions who attend to the scene of acutely ill patients. This opens three interesting avenues of research:

1.3.1 Geospatial

Due to the need to find patients, modern paramedic records contain very specific and accurate geospatial data. With the integration of computer-aided dispatching which cross-validates addresses from 911 caller, to live digital linkages between paramedic terminals and dispatch computers, to GPS tracking of paramedic vehicles, this data has enormous potential for research not previously possible using paramedic data. This potential includes better operational models such as optimal deployment plans for road-based ambulances [18], [19] or even models to plan for future drone technology [20]. The use of geospatial data also has potential outside of the traditional realm of paramedic operational research. By integrating paramedic clinical findings and environmental data, research into patient-centered models examining the potential causative factors of pollution becomes possible [21], [22].

1.3.2 Refusal patients

Paramedics see a significant number of patients that are not seen by other healthcare agencies. Previous studies have shown that the rate of non-transport varies from 11%-56% [23]–[25] and that, for certain pathologies, non-transport is a safe alternative to transport to the ED

[23], [24], [26]. Since these patients are not seen in a traditional hospital, they are often missed in hospital-based studies of patient populations.

There has also recently been an increased interest in the concept of “treat-n-refer” or “treat-n-release” protocols for paramedics as a cost-effective way to alleviate ED overcrowding [27]. While these programs are not new, they are new to Ontario which is currently implementing its first large-scale treat-n-release program for palliative patients. As programs like this come online and the paramedic skill set continues to expand, the number of non-transports will continue to grow increasing the number of patients who are only captured in paramedic data.

1.3.3 The not-so-sick-any-more patient.

> ED Nurse: "*What's the rush? They don't look that sick.*"
>
> Very tired and stressed-looking Paramedic: "*You should have seen them when I met them.*"

As paramedic skill sets have increased, the ability for paramedics to affect patient outcomes has also increased [28]. Each year paramedics are implementing new treatments and new equipment which more closely interconnects with the treatment provided in other areas of medicine [29]. As these new modalities come online, more and more patients are seeing improvements in their condition prior to reaching hospital [30]–[32], meaning the data necessary for even basic inclusion criteria is increasingly having to be pulled from paramedic data. However, this requires hospital records and outcomes to be linked to paramedic records which typically is a slow and expensive manual process [33]. While probabilistic matching has shown promise in some datasets [34], [35] the accuracy relies heavily on the completeness of the paramedic dataset [36]. The creation of strong and automated data linkages, along with tidy well-formatted paramedic data, will greatly increase the success, while reducing the human, computational and financial resources necessary for ongoing research.

1.4 A project-based approach

While paramedic data has some significant hurdles to its use, we have just seen that it also has significant potential. The lack of established processes for data management and data cleaning within paramedicine, along with a very limited number of data science experts with the requisite paramedic-specific domain knowledge has hampered the forward progress of paramedicine into the medical discipline that it could be. This thesis will serve as a starting block to help overcome the hurdles of paramedic data while bringing needed insight to what paramedic data can contribute to the world of health care.

To give this thesis direction and form, I have chosen to take a project-based approach to facilitate the development of the knowledge and techniques necessary to tackle the hurdles of paramedic data. That project is the opioid crisis. At the time this thesis was started (September 2019) morbidity and mortality related to opioid overdoses were one of the largest public health concerns facing the nation. While the opioid crisis was soon to be overshadowed by the COVID-19 pandemic, the harms of opioids and other drugs have not magically disappeared but have simply been shifted to the background. Paramedics see the harms inflicted on society by opioids and other drugs on a daily basis and, as we will see in this thesis, the data paramedics create, when properly cleaned and analyzed, has many valuable insights into this world.

Chapter 2

Data Cleaning

2.1 Data sources

2.1.1 The Paramedic Services

The data for this thesis is provided by three Paramedic services local to Peterborough and the Kawarthas. They are:

- Peterborough County/City Paramedic Service
- Kawartha Lakes Paramedic Service
- Halliburton Paramedic Service

Peterborough County/City Paramedic Service

Peterborough County/City Paramedics (PCCP) provides coverage to the County of Peterborough and the City of Peterborough[1]. The joint population is $\sim$ 134,000 people as of the 2016 census (82,000 in city and 52,000 in county [37], [38]). At the time of publishing, PCCP operated seven 24-hour/day ambulances and three

[1] The City and County are both Upper Tier Municipalities. The service is jointly run under a shared service agreement but is administered by the county.

12-hour/day “day-car” ambulances (07:00-19:00, 08:00-20:00 and 09:00-21:00) from 5 full-time stations and 1 seasonal station; the seasonal station operates as a day-only station from approximately Easter to Thanksgiving.

PCCP was the original contributor for this research and is the focus of the earlier phases of the opioid examination. As such most of the data processing techniques were developed using PCCP data and then expanded and adapted to include other services as new services came online and received ethics approval. While PCCP has granted open access on a project by project bases, this thesis only includes data for 2016-2019.

Kawartha Lakes Paramedic Service

Kawartha Lakes Paramedic Service (KLPS) provides coverage to the city of Kawartha Lakes (previously known as Victoria County). KLPS serves a population of ˜75,000 people as of the 2016 census [39]. At the time of publishing, KLPS operated six 24-hour/day ambulances and one 12-hour/day “day-car” ambulance, plus an additional day car from Friday–Sunday.

KLPS began contributing data in April 2021 but allowed for retrospective access to 2016.

Haliburton Paramedic Service

Haliburton Paramedic Service (HPS) Provides coverage for the county of Haliburton. HPS services a population of $\sim$ 18,000 as of the 2016 census [40]. At the time of publishing, HPS operated three 24hour/day ambulances and one 12-hour “day-car” ambulance (11:00-23:00).

HPS began contributing data in April 2021 but allowed for retrospective access to 2016.

2.1.2 Car Counts

While the deployment details described above are accurate for a normally staffed shift at each service as of the time of publishing, they do not take into account additional vehicles that may have been added to the car count as temporary service enhancements, down staffing of units due to lack of staff or mechanical problems, or extra coverage put in place to account for special events or surge demand. Since the analysis presented here focuses primarily on overall call volumes and patient demographics and does not consider analysis that could require a more precise car count (i.e.: unit hour utilization, paramedic workloads, differential response times) this information is provided for familiarity purposes only.

These numbers also do not account for Paramedic Response Units. A Paramedic Response Unit is the term for a single paramedic in a non-ambulance response vehicle. In most regions these response units are SUVs, however, they can also be other vehicles like cars or pick-up trucks depending on the needs of the region. It is important to note that while these response vehicles can not transport a patient, they do carry all the same medical equipment that an ambulance does. Their primary function is to respond rapidly to scene and provide patient care while waiting for a fully staffed ambulance to transport. In rare circumstances, a Supervisor may respond to calls as a Paramedic Response Unit. This most commonly occurs when the Supervisor is exceptionally close to a critical call or when paramedic resources are severely depleted due to call volumes, however these circumstances will vary between services. Paramedic Response Units will be further discussed when it comes to cleaning of duplicate calls later in this chapter.

2.1.3 PCR database

All three paramedic services contract with Interdev Technologies' to provide the iMedic program for their PCR service. Once data is entered by paramedics, the information is transferred to Interdev's servers for storage and archiving. The PCR can then be accessed online as both a complete form (as a webpage or PDF) or as part of a SQL database. Unfortunately, the SQL database is not one single data frame for all records but is multiple databases for different aspects of the PCR which are then linked by a `TransportID`. The `TransportID` is the unique identifier for each record.

2.2 Ethics

Ethics approval for this thesis was granted by Trent University's Research Ethics Board (File# 25947 and 26516). None of the paramedic services or municipalities contributing data to this thesis have internal Research Ethics Boards. All three services accepted Trent's Research Ethics Board's approval as satisfying the condition of the Personal Health Information Protection Act, RSO 2019, s44(1).

2.3 Data Access and Export

Data for this thesis was accessed via Interdev's online portal using Microsoft EasyView (essentially a version of MS Access). Data queries were created in SQL (see code sample below) and then exported from EasyView as MS Excel (.xlsx) files. Once in Excel, the files were then converted to CSV files for reading into R. While converting to CSV files added an extra step, the choice to use CSV over Excel files was made to promote forward compatibility and help support inputs from other PCR programs in the future.

```sql
SELECT dbo_AcrData.[Call Date], dbo_ACRProceduresGrid.Code,
  dbo_AcrData.TransportID, dbo_ACRProceduresGrid.Crew
FROM dbo_ACRProceduresGrid INNER JOIN dbo_AcrData ON
  dbo_ACRProceduresGrid.TransportID = dbo_AcrData.TransportID
WHERE (((dbo_AcrData.[Call Date]) Between #1/1/2016# And #12/31/2020#)
      AND ((dbo_ACRProceduresGrid.Code)="610"));
```

Due to the structure of Interdev's databases as multiple linked databases, multiple separate smaller queries were run within each service's ACR database and then linked in R at a later point in time. One query addressed generic patient and temporal data points. A second query addressed naloxone prior to paramedic arrival, and a third query addressed patients receiving naloxone from a paramedic (the purpose of these data points will be explained in Chapter 3). While it may have been possible to query all data points with improved SQL skills, all attempts to do so caused the Interdev server to lock up or kick me out of the remote session. For the purposes of stable data access and expediency, it was easier to export the data separately and then link it later. Each of these queries was then repeated for each service, as each service maintains a separate database within the Interdev system.

Table 2.1. Count and percentage of missingness of key datum for study populations.

	n	Age	Age(%)	Sex	Sex(%)	UTM	UTM(%)	Pick-Up Loc	Pick-up Loc(%)
Opioid Overdose	526	9	1.7%	2	0.4%	5	1.0%	0	0.0%
Non-Opioid Overdose	455	2	0.4%	2	0.4%	5	1.1%	0	0.0%
Alcohol Intoxication	1539	20	1.3%	9	0.6%	11	0.7%	0	0.0%
Non-Intoxication	51631	390	0.8%	404	0.8%	541	1.0%	18	0.0%

In addition to running separate queries for each service, EasyView limits an export to no more than about 64,000 records, necessitating multiple queries due to the number of records. PCCP and KLPS data were exported in 1-year increments, while HPS data, due to its smaller call volumes, was exported in 2-year increments. When the study was expanded to include 2020 and 2021 data, all services were exported in 1-year increments to allow for conformity and a single string of code to be used, rather than having to develop separate codes for each system.

2.4 Missing Data

With the consideration of the discussion on missing data in Chapter 1, it was important to examine the missingness of the data points used in this thesis. Table 2.1 describes the missing data within the demographics for the various populations that will be discussed in this thesis. It is interesting to note that the proportion of missing ages for the opioid and alcohol intoxication population are both significantly larger than that of the non-intox population (p-value: 0.0244 and $p < 0.001$ respectively). One possible reason for this is that these two populations are more likely to be unconscious and not carrying identification compared to the non-intox population, thus making it hard to determine a date of birth or age. If this is true, then at least some of the missingness of age for the opioid and alcohol population would be Not Missing at Random as the data being missing is a direct result of their condition. However, due to the small proportions of missing data and the fact that most comparisons in this thesis are within a population, it is not likely to have an impact on the analysis within this thesis [6].

2.4.1 Limited Data collection

Throughout medical and pre-hospital research, there are a wide variety of different types of data collected. Some are unique to the system being studied, while others are more broadly collected. One datum that is distinctly missing from Ontario paramedic data is the collection of racial/ethnic data. Previous studies, mostly in the USA, have found that race/ethnicity do play a part in the usage of paramedic resources [41] and that race/ethnicity do show specific correlations to mortality [42], opioid vs other drug use [43], and geospatial distributions [44]. This thesis will not consider any racial or ethnic data as no Canadian paramedic service collects this data. This is not to say that these racial disparities do not exist in Canada, but one can only study the data that is collected.

Another important consideration is the patient's sex described within this thesis. The Ontario ACR allows for an "M," "F" or "X" option when designating a patient's sex and the ACR completion manual states that the sex documented should reflect what is printed on the patients provincial health card [13]. However, the "X" seems to be very rarely used. In fact it represents only 0.05% of the overall patient population and only one patient within any of the sub-populations examined in this thesis. As such this thesis will only consider the "M" and "F" sexes due to the lack of representation for those who identify as a descriptor other than male or female.

2.5 Data Cleaning

2.5.1 Removal of unwanted and duplicate calls

When examining any dataset there are often unwanted elements within the data, and this is true for paramedic data as well. It is important to remember that the ACR stands for Ambulance Call Report, and while Ontario uses it as (and it is primarily designed as) our PCR (Patient Care Report) it is also used to document all paramedic movements and activities. Each call for service or vehicle movement is assigned a unique call number by the Central Ambulance Communication Center (ambulance dispatch) and each call number must have at least 1 ACR associated with it. This includes when an ambulance is assigned a call and cancelled 20 seconds later due to a closer unit being available; when an ambulance arrives on scene and finds no patient; or when an ambulance is assigned to a different coverage area/different base as emergency coverage while the ambulance native to that area is busy. While these records are important and may have value in some future study, they are not necessarily important to this thesis and because of this must be removed from the dataset to prevent interference with analysis.

No patient calls

As mentioned above, there are several circumstances when ACRs are generated where no patients are involved. In the case of a paramedic unit being cancelled prior to arrival on scene or a unit being assigned to an alternate coverage area, these ACRs are generated automatically by a linkage between the Central Ambulance Communication Center computer system and Interdev's servers. In the case of a paramedic unit arriving on scene and finding no patient, the paramedics are required to do a "no patient found" ACR stating that they arrived and what they saw and did while on scene. The narrative for this type of ACR might include something like

> "Called for unconscious person in front of bank, on arrival found no patient. Bystander states person was sleeping and got up and ran away when they heard the siren, crew were unable to locate anyone who appeared in need of assistance."

All three of these call types have specific and unique coding associated with them which allowed for easy filtering of these records.

Duplicate calls

Another requirement of Ontario paramedics is that each vehicle must complete an ACR for each patient they assess or treat, even if that patient is transported by another ambulance. The most common circumstance for this situation is where the first arriving paramedic is in a Paramedic Response Unit and is unable to transport a patient. The other common situation would be a multi-casualty incident, which is where the number of patients exceeds the on-scene resources (e.g., multi-vehicle motor vehicle collision). In this circumstance, the first arriving paramedics would assess and start treatment on multiple patients while waiting for secondary units to arrive and take over care. In both instances, the proper documentation technique would be for the first arriving paramedic(s) to complete a separate ACR for each patient they have treated which covers the time from patient contact until they transfer care to the secondary paramedic unit. This secondary unit would then do a second ACR covering the treatment they provided from the time they met the patient until patient care was transferred to the ER. In the case of an MCI with 5 patients, this could mean that 10 ACRs would be associated with a single Call Number, with each ACR having its own unique Transport ID, but those 10 Transport IDs would represent only 5 patients. Depending on how individual patients are identified within a study, the inclusion of duplicate patients could significantly affect the results.

Luckily this circumstance is relatively easy to resolve within the limited objectives of this thesis. When a paramedic hands a patient over to another crew, the specific `Return Priority Code` of 75 (Transport by Other Ambulance) is used. By using this code as a filter to remove all PCRs for the first arriving paramedic, only the transporting paramedic's PCRs would be retained eliminating any duplication. Unfortunately, this means any information from the first PCR would be lost to the analysis. For the purposes of this thesis, the loss of data should not present a problem. The demographics and call date/time should not vary between PCRs and any treatment provided prior to arrival that would be relevant to this thesis should be documented in the secondary PCRs as a practice of good documentation (the specifics of this will be discussed in Chapter 3).

For future research where the loss of data due to removal of duplicate records for the same patient would have an impact on data quality, it would be possible to link the primary and secondary PCR using patient identifiers prior to removing the primary PCR thus allowing necessary data elements to be retained. However, the use of patient identifiers requires a significantly more complicated ethics approval due to the risk of potential data security breaches when using patient identifiers. It may also be possible to link the primary and secondary ACR using probabilistic linking based on non-identifying demographics such as age and sex as well as date/time fields.

However, this approach would require significant testing to ensure that a) only the necessary elements were retained b) that other important data was not duplicated and c) that the linkage can reliably connect patient records. This last step may be the most difficult as in my experience, it is not uncommon to have multiple patients with very similar demographics in an MCI (e.g., MVC with four 18-year-old males). While I still believe that probabilistic linkages can be built that can overcome these circumstances, further research is needed.

2.5.2 Adjustments to datum

Due to the design of the ACR certain data points of the dataset needed to be adjusted to align with proper tidy data practices.

Age

One example of this is patient age. While the `Age` data point appears as a numerical variable, it is actually a calculated variable within the iMedic program. The age calculation is based on the call date and the patient's date of birth and allows for a numerical range of 1 to 150[2]. However, one thing that is not obvious is the ACR stores the age in different units depending on the patient's age per the criteria in Table 2.2 [13]. These units are labelled in a separate data point called `AgeUnit` which could easily be missed when examining the data structure, leading one to the logical assumption all ages are documented in years. For this dataset all ages were converted to years, with ages $<$ 12 months being set to an age of zero years and all ages $\geq$ 12 months but $<$ 24 months being set to 1 year of age. All ages $>$ 24 months are already in years and have been left as is. While it may seem that a data point which

[2]Interdev limits the age value to 150 years.

Table 2.2. Table describing the limits of age units within the ACR system.

Display Unit	Label	Lower Limit	Upper Limit
Days	d	1 day	$\leq$ 31 day
Weeks	wks	$>$ 31 days	$\leq$ 12 weeks
Months	mths	$>$ 12 weeks	$\leq$ 24 months
Years	yrs	$>$ 24 months	$\leq$ 150 years

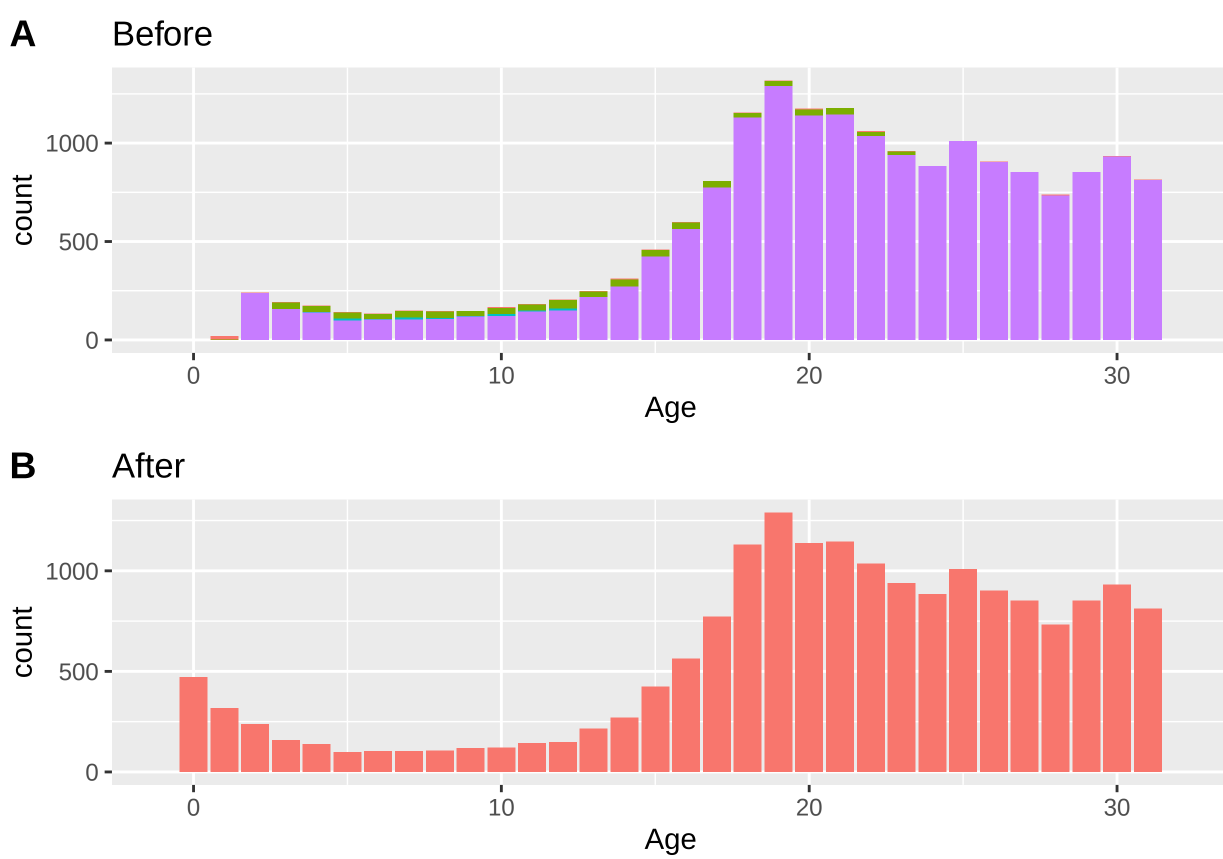

Figure 2.1. Age distribution of all patients, before (A) and after (B) correction of age muti-unit system in iMedic. Colour of stacked bars in (A) represent different units of measure.

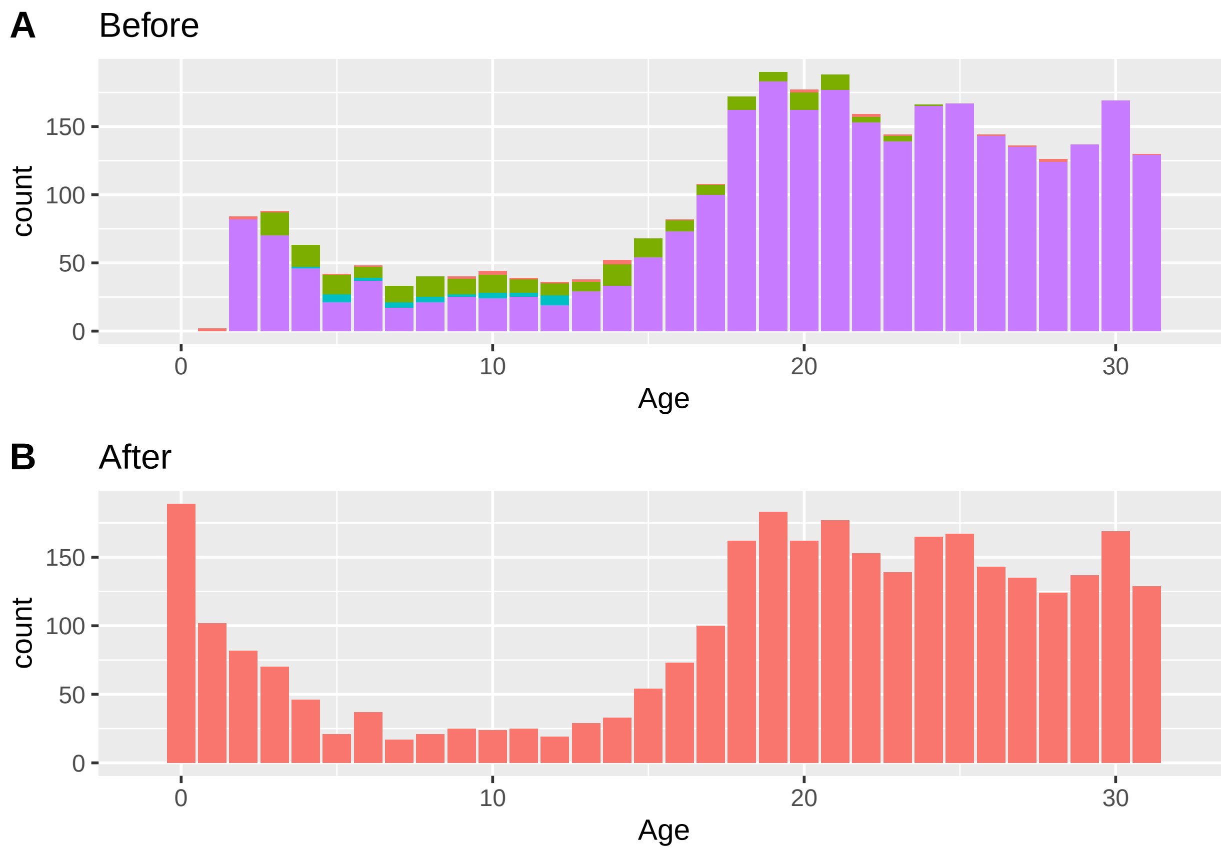

Figure 2.2. Age distribution of 4 most common problem types for pediatirc patients <2 years of age, before (A) and after (B) correction of age muti-unit system in iMedic. Colour of stacked bars in (A) represent different units measure.

affects only those under 2 years of age (0.8% of PCCP patients) is inconsequential, the integration of values with different units into a single data point actually introduces an artificial central tenancy leading to a statistically significant upward bias in the age distributions for all cases between 3 and 31 years of age (p-value: $p < 0.001$) which accounts for 19.5% of the patient population. This effect will also vary depending on the problem being examined as certain call types are more common in pediatric patients. Figure 2.1 displays the age distribution from age 0-31 years before and after the correction for all cases, while figure 2.2 displays the age distribution before and after the correction for the 4 problem codes most common in those under 2 years of age. While the distributions are distinctly different in both figures, the effect is much more pronounced in figure 2.2. For those cases over 31 years of age, there is no significant impact of the age correction (p-value: 1)

Review of free text narratives.

Free text narrative data is a necessity in paramedic PCRs; however, it is also one of the areas that makes paramedic data so hard to work with. While paramedics typically have very structured PCRs to capture critical data points, the unpredictable nature of paramedicine makes it nearly impossible to write a single form that can encompass all the possible calls a paramedic may do. For example:

> I witnessed a car rollover one day while driving back to the station at work. While the medical assessment was fairly straightforward, having to explain why we were significantly delayed for extrication on scene and then needed to return to the station to shower and change our uniforms was not. In this case, the driver's unrestrained cats became very upset mid-high-speed rollover and proceeded to explosively defecate in the rolling car, coating every surface in feline fecal material.

While this is an odd example, it captures the weirdness of paramedicine nicely. Important elements of research data are also often contained in free text narratives. This is especially true for emerging areas of research that were not common prior to the last update of the PCR system.

One example of this that is relevant to this thesis is the use of naloxone Prior to Arrival (PTA). Naloxone is a safe and effective competitive opioid antagonist used both in and out of hospital for the reversal of opioid overdoses [47]. Better known in Canada by its trade name, Narcan, naloxone in now available to members of the community in take-home Narcan kits [48]. Prior to the last major update to the ACR in 2016, naloxone was very rarely seen outside of medical circles. Since that time, Narcan kits have become increasingly common. In order to examine the effects of naloxone PTA on paramedic naloxone administration (see Chapter 3 – Metrics) we first had to identify which patients received naloxone PTA and from whom. This data is most commonly documented in the Treatment Prior to Arrival section of the ACR which includes a free text narrative text box and a list of checkboxes for who provided the treatment described in the narrative.

All free-text narratives within the iMedic system are stored in a separate database linked by `TransportID`. Due to this separate database, naloxone PTA data was pulled via a separate query using the SQL code below which preformed a text search for the terms “naloxone” and “Narcan” in the Treatment Prior to Arrival naratives of all ACRs.

```
SELECT dbo_AcrData.TransportID, dbo_AcrData.[Call Number/Patient
      Number],
  dbo_AcrData.[Call Date], dbo_AcrData.TreatmentPriorToArrival,
  dbo_ACRText.TreatmentPriorToArrivalComments
FROM dbo_AcrData INNER JOIN dbo_ACRText ON dbo_AcrData.TransportID =
      dbo_ACRText.TransportID
WHERE (((dbo_AcrData.[Call Date]) Between #1/1/2016# And #12/31/2020#)
      AND
  ((dbo_ACRText.TreatmentPriorToArrivalComments) Like "*" & "narcan" &
      "*")) OR
  (((dbo_AcrData.[Call Date]) Between #1/1/2016# And #12/31/2020#) AND
```

Figure 2.3. Sample image of the Treatment Prior to Arrival narrative section of the ACR (iMedic platform).

Figure 2.4. Sample image of the dropdown menu from the Treatment Prior to Arrival area of the ACR (iMedic platform) with check boxes for indicating which agency provided the treatment.

```
((dbo_ACRText.TreatmentPriorToArrivalComments) Like "*" & "naloxone"
    & "*"));
```

While this search specifically pulled cases with the keywords, it cannot interpret the sentence structure around their use. Specifically for this analysis, it could not recognize negative sentence structure (i.e., "friend *could not* find Narcan kit" or "Narcan next to patient but *not* used) nor could it determine who administered the naloxone. While the Treatment Prior to Arrival section of the ACR has different checkboxes for who administered the treatment (see Figure 2.3) these providers are not directly linked to their actions within the PCR. As well, when multiple agencies have provided treatment prior to paramedic arrival, all those who are checked off are stored jointly as a single character variable (ex: "Police,Fire,Other"). Due to the data structure of all these agencies/providers being stored in a single data point and the lack of any linkage between provider and treatment, R is not able to separate who did what. However, this information is normally discernible within the narrative with a little careful reading. While it would likely have been possible to “read” the free text with machine learning and natural language processing [49] for the small number of records in this thesis it seemed most expedient to just manually review them.

For the review, the data was pulled into MS Excel and reviewed for the two key data points of was naloxone given and who gave it. For the purposes of reproducibility and accountability, cases with negative sentence structure were removed individually, with the relevant narrative text included below the relevant code. (see the redacted example below). This was possible due to the relatively small number of cases that fell in this category (12 cases).

```
NarcanTxPA_PCCP<- NarcanTxPA_PCCP[-which(Narc anTxPA_PCCP$TransportID
      == "733###########"),]
#Text states "no naloxone was given"
```

For cases where the naloxone provider had to be clarified, it rapidly became clear that due to the number of cases it would be unmanageable to follow the same process as was used for negative sentence structure. For these cases, the `TransportID` of the cases that needed to have the naloxone provider corrected were copied into a separate excel file, with each column representing a different provider. This new listing of `Transport ID` was then read into R and the relevant cases were modified using

The process of listing `TransportID` as a separate data frame also had the benefit of being easily expandable as new cases were added when the study time frames were extended to include 2020 and 2021. Rather than having to manually redo the review of all cases or having to join separate files for each expansion, the listings of `TransportID` could just be expanded and the same code can be reused to update the data.

For the unique case of KLPS and the Central East Correctional Center, all cases that originated from within the institution were separated into a new category "CECC." The policies and processes for the management of overdoses within the institution are different from practice in the general public. As such any findings there would need to be examined independently which was not within the scope of this thesis.

Pick-up Location

The ACR Pick-up Location code is an alphabetic code that specifies the type of location an ambulance is called to. These are stored within the iMedic system as both the code (`Pick.Up.Location.Code`) and the descriptor for the location type (`PickupLocationDescription`). There are 26 options (A-Z) and include commonly used ones like R for House/Townhouse, S for Street/Hwy/Road and B for Apartment/Condo and less commonly used ones like C for Construction Site and F for Factory/Industrial Site/Railway/Dockyard. (A full listing is available in Appendix A). However, like most things in the ACR, there are no definitions for these codes meaning the difference between a Long-Term Care Home (N) and a Retirement Home (U) is left to the discretion of each paramedic.

These codes have also been updated over time by the Ministry of Health, with the most recent update happening in mid to late 2016. One example of this is U which in older versions of the ACR referred to a Stadium but was updated to refer to a

Retirement Home[3]. Conveniently, the iMedic system labels legacy codes (such as U prior to the update) differently from newer entries, (i.e., U0 versus U) which makes them easy to identify and adjust. For consistency and ease of analysis, these legacy codes were modified to match the current coding system. Where the new codes do not have a direct equivalent, the legacy codes were linked with their most logical modern equivalent (e.g., stadium was included with Sports Facility/Arena (P)). For the sake of maintaining the original source data, the `PickupLocationDescription` were not changed so all analysis relies on the use of the `Pick.Up.Location.Code`.

```
AllCall_PCCP$Pick.Up.Location.Code [which
      (AllCall_PCCP$Pick.Up.Location.Code == "U0")] <- "P"
```

Another component of the 2016 update to the ACR was converting pick-up location from a two-digit alphanumeric code to a single-digit alphabetic code. Prior to the update, the second position of the alphanumeric code was a two options numeric component (0 or 3) that was used to discern locations that were ≥ 3 stories or < 3 stores. While the pick-up location height was found to have limited value in work on vertical response [50] it was ultimately scrapped as being uninformative as the lack of a definition again caused issues (ie: does the height refer to the building itself or what floor the call happened on). Since the vertical response was not a component of any analysis for this thesis, and only a small proportion of the oldest data had the vertical component, all `Pick.Up.Location.Code` were modified to link with the modern single-digit alphabetical equivalent, using code similar to this example:

[3] Prior to the update, there was no option for retirement home.

```
AllCall_PCCP$Pick.Up.Location.Code[which(
      AllCall_PCCP$Pick.Up.Location.Code == "A3")] <- "A"
```

One other necessary adjustment was due to a design flaw in the iMedic ACR interface. The iMedic ACR program is designed for quick and easy use and allows paramedics to tab through the various fields and has an auto-populate feature whereby hitting the first letter of your desired entry, the field will auto-populate with the first item in the list that starts with that letter. However, for Pick-up Location, the field is very small on screen, only showing the first 5 or 6 characters of the names. One very common location for a paramedic call is a long-term care home (better known and previously coded as a "Nursing Home"). For many paramedics who worked prior to the change in location options (and those who learned how to complete an ACR from them) it is a habit to hit "N" for nursing home when completing an ACR. However, in the updated system, N brings up "Nursing Outpost," but due to the small field in iMedic all the paramedic sees is "Nursei." The PCCP dataset has 1747 cases coded as Nursing Outpost. Since Peterborough County does not have any nursing outposts (nor do any of the surrounding counties/regions) the vast majority, if not all of these cases are logically an error in data entry due to the poor interface. To correct this error, the `Pick.Up.Location.Code` for all cases where Nursing Outpost was documented were adjusted to read "N" for Long-Term Care Home. The `PickupLocationDescription` were again left to maintain the original source data.

Chapter 3

Metrics

Acknowledgement: This chapter is derived in part from an article published in Prehospital Emergency Care, January 24th, 2022. Copyright NAEMSP. Original article available online: http://www.tandfonline.com/10.1080/10903127.2022.2033895

As mentioned in Chapter 1, the choice of data points is key when working in paramedic data. The most important is what data point will serve as the key metric. In some cases, the choice is obvious. For instance, when reporting response times the Ontario Government has set a clear guideline for response time to be reported based on patient acuity on the Canadian Triage Acuity Scale (CTAS) [51]. CTAS has very well-defined determination criteria [52] and significant validation behind its use [53], [54]. Response times are also clearly defined in the published reporting structure. With clearly defined variables and well-established data points, it is possible to create very clear values which should have strong inter-rater reliability between services[1].

[1] This is not a comment on the validity of response times as a metric, but instead made to point out that choice of datum in the metric is at least based on well defined criteria.

However, the most obvious choice is not always the correct choice for more complicated areas of study due to the variability in documentation styles and lack of a data dictionary. A prime example of this in the opioid overdose field is what metrics should be used to identify opioid overdoses.

Current government monitoring tools rely largely on emergency department visits and deaths as related by Coroner data [55], [56]. While useful tools, both methods have limitations in their ability to fully capture the true scope of the opioid crisis. Coroner data in certain US states has previously been shown to miss up to 50% of opioid-related deaths due to lack of proper testing [57]. Release of Coroner data is also commonly delayed 3-12 months [55] due to the need to complete investigations prior to releasing case counts [56]. While emergency department visits are reported in a timelier manner and have not previously been reported to have a large false-negative rate, emergency departments can only report on the cases which are seen in their facility. Some people who use (non-legalized) drugs are known to avoid ED visits due to fear of stigmatization or police involvement/criminal charges [58], [59].

Paramedic data has recently emerged as a possible way to fill gaps in the monitoring of opioid-related harms [45]. As previously discussed, paramedics are commonly the first medical personnel called to overdoses [60], largely use electronic patient care records (ePCR) making data readily accessible and are adept at identifying and treating opioid overdoses. As such, paramedic data is ideally suited for real-time monitoring [60], [61]. Paramedics are also one of the few medical personnel who travel to the patient which allows for geographic monitoring [22]. The question then becomes what components of paramedic data are best suited to serve as a proxy metric for community opioid overdoses. In order to be a useful public health metric, a data point must be able to 1) detect change over time, 2) have validity, 3) be sensitive to health policy changes and 4) be reliable and stable over time [62]. One data point currently being used in many areas is Paramedic Naloxone, which is where a paramedic administered naloxone as part of their treatment of a patient. Previous work on the use of paramedic naloxone as a metric for opioid overdose has shown mixed results. While many studies have found paramedic naloxone capable of detecting temporal and geographic trends [63]–[66] other work has questioned the sensitivity and specificity of paramedic naloxone. Grover *et al.* [63], found that paramedic naloxone captured only 57% of probable opioid overdoses, with a positive predictive value of 60%.

Naloxone is a safe and effective opioid antagonist commonly used both in and out of hospital for the reversal of opioid overdoses [46]. In Ontario, Canada (pre-Covid), paramedics could consider administering naloxone when they suspected an opioid overdose and when there is an inability to effectively ventilate the patient for either a clinical or operational reason [67]. Since 2016, naloxone has been increasingly made available (free of charge) to members of the public by local public health agencies in the form of take-home naloxone kits. Today take-home kits are available from most emergency departments, pharmacies and community services that support or interact with people who use drugs [48], [68]. There is even a provincial website that allows people to search for the closest naloxone distribution site via mapping software [48]. Anecdotal reports from frontline paramedics have indicated bystander naloxone administration has increased dramatically since 2016, including comments such as 'most of our patients get [administered naloxone] by someone before we get there.'

This is supported by research showing that 94% of patients who received naloxone prior to paramedic arrival saw clinical improvement prior to hospital arrival with no further naloxone from paramedics. [69]

The aim of this chapter was to determine if paramedic naloxone, when used in isolation, is an effective proxy metric for the monitoring of community opioid overdose. A secondary objective was to determine what effects, if any, that take-home naloxone kits may have on the use of paramedic naloxone as a metric.

3.1 Methods

For this analysis, the ePCRs for PCCP were examined from January 1, 2016 to December 31, 2019. All cases with a primary, secondary, or final problem code of Suspected Opioid Overdose along with all patients who were documented to have been administered naloxone by a paramedic, were included in this analysis. To examine the influences of take-home naloxone kits, those cases who received bystander naloxone as determined by a review of the free-text narrative section of the Treatment Prior to Arrival area of the ACR were also examined. (The methods for free-text narrative review were outlined in section *2.5.2.2 Review of free text narratives.*)

Patient age was analyzed using a chi-square test, while weight and sex were analyzed using Welch t-tests. Temporal analysis of opioid overdoses was conducted on the year, month, day-of-month and hour-of-day time frames using Chi-squared tests based on the date and time the 911 call was received by the Central Ambulance Communication Center. Overdose locations were examined using the ePCR location description code, which provides 26 possible location types (see appendix A, for a full listing of location codes). The population was divided into two sub-populations, those who did and those who did not receive paramedic naloxone, and cases were then further categorized into 4 groups: house (including townhouse); apartment; street; or public place, based on their similarity of location categories, operational realities of the various location types and the local environment. These four location groups were then analyzed using Chi-squared for the sub-population comparison followed by Bonferroni-adjusted post-hoc proportion tests (adjusted significance clip set to $P < 0.0125$) for the individual location category comparisons. This location comparison was also completed for bystander naloxone.

3.2 Results

During the 4 years of the study, PCCP reported 70132 patient contacts, of which 573 ePCRs were documented with an opioid problem code, while 171 doses of naloxone were administered by paramedics. After filtering for duplicate PCRs and multiple doses of naloxone, 559 cases were identified as opioid overdoses, of these significantly fewer (124, $p < 0.001$) received paramedic naloxone in the pre-hospital environment.

The mean age of the opioid overdose population in this study was 37.85 years with 28% of the cases being female. The average weight of an opioid overdose case was 78kg.

3.2.1 Paramedic naloxone

In comparing those cases who did and those cases who did not receive paramedic naloxone, no significant difference in sex, age or weight were found. (p-values: 1, 0.2804, 0.2554 respectively.)

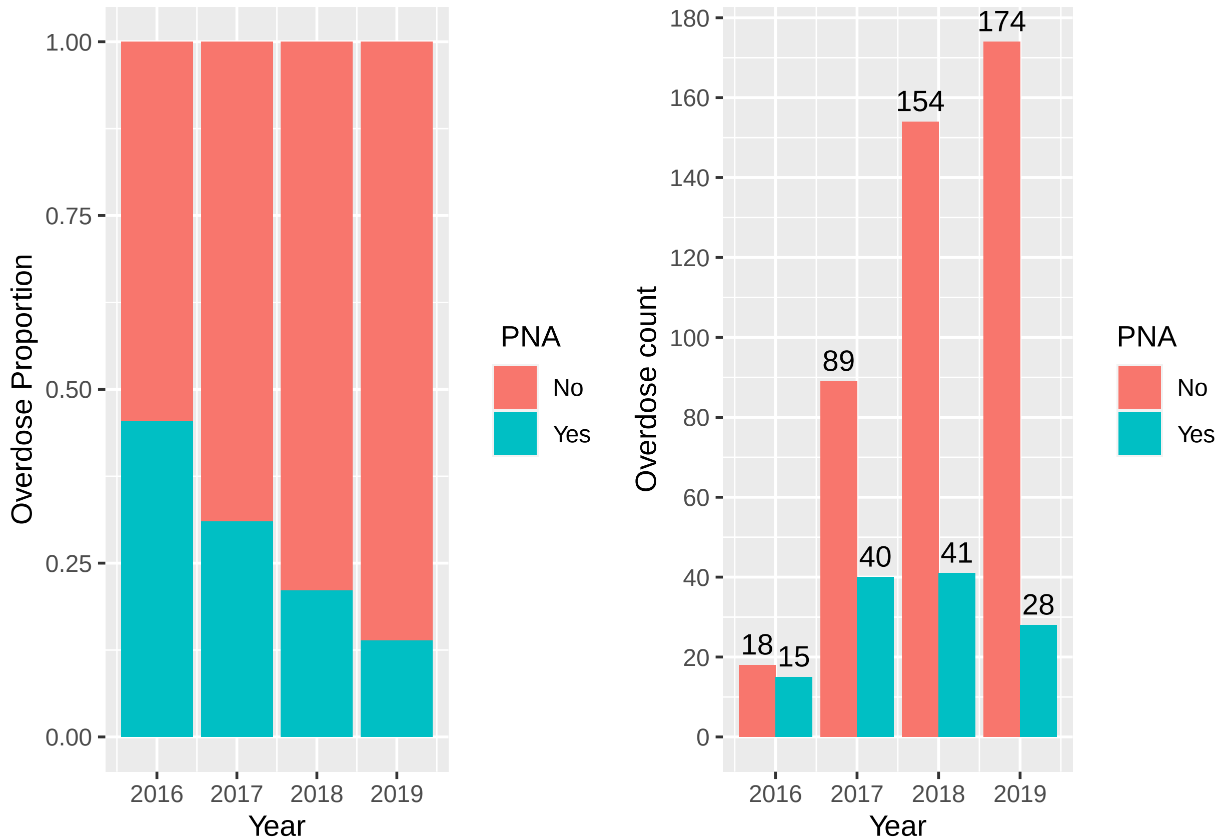

Figure 3.1. Proportion (Left) and count (Right) of PNA vs non-PNA opioid overdose calls from 2016-2019.

When the type of location was examined, paramedic naloxone was found to have a statistically significant positive association with "House" (56% vs 37%, $p < 0.001$) but was negatively associated with public places (4.8% vs 14%, p: 0.0088). On a street location, paramedic naloxone cases also occurred at a lower rate than cases where the attending paramedic did not give naloxone (6% vs 13.3%), although not significantly so. Cases in apartments were not significantly different (27% vs 22%, p: 0.3774). Analysis of the cases against a temporal viewpoint found that despite increasing overall call volumes and increasing opioid overdose cases from 2016 to 2019, the proportion of opioid overdose patients receiving paramedic naloxone decreased annually ($p < 0.001$) (see Figure 3.1).

No other significant temporal differences in case counts in time of day (hour), day of week, day of month or month of the year were observed when comparing cases which did an did not receive paramedic naloxone.

3.2.2 Bystander naloxone

In the search of the "Treatment Prior to Arrival" field of the ePCR, 278 cases were identified as including the word "naloxone" or "Narcan." On manual review, 6 cases were removed as the free text referred to not giving naloxone (e.g., "friends couldn't find [naloxone kit]"). Ten cases were removed as duplication due to multiple responding units and 81 cases were removed as they were not associated with an identified opioid overdose.

This left 181 (32%) of opioid overdoses in this study identified as having received naloxone Prior to Arrival (PTA).

All cases of bystander naloxone were initially examined independently of any association with identified opioid overdose for trends in the use of naloxone by non-paramedics. Naloxone was administered primarily by bystanders (246 cases), followed distantly by fire department first responders (25 cases) and police (4 cases). Dosage and route varied between 0.4 and 8.0mg with most doses (where information was available) having been given intranasal, although dosage and route were often not documented. While there was no statistical difference in age, sex, or weights between

Table 3.1. Demographics of opioid overdose divided into those cases who received bystander naloxone and those cases who did not. In each row, the p-values refer to tests comparing the two populations (e.g., t-tests for the difference in means for Age and Weight; proportion tests for differences in location or Gender).

	Bystander naloxone	No bystander naloxone	p value
n	181	378	p less than 0.001
Age (yrs)	36.9	38.3	0.1896
Gender (%F)	26%	30%	0.4249
Weight (kg)	76.2	79.4	0.1459
Location			
- House	41	42	0.8972
- Apt	22.8	24.3	0.7634
- Street	14.3	6.6	0.013
- Public Place	22	27.1	0.2203

those who did and did not receive bystander naloxone (Table 3.1), there was a fatalistically significant difference in the types of locations (p: 0.0265). In a post-hoc analysis, only those cases in a "street" were found to be significantly different (p: 0.013) with 6.6% receiving bystander naloxone versus 14.3% who did not. A statistically significant increase in bystander naloxone was found in more recent years (p: <0.001) (Figure 3.2), but no other significant differences were found in other temporal analyses.

3.3 Discussion

Our findings suggest that paramedic naloxone, when used independently, is of limited use as a metric for monitoring community opioid overdoses as it does not meet any of the criteria for an effective metric. In our system, only 22% of identified opioid overdoses were treated by a paramedic with naloxone and each year a smaller proportion of cases were treated with paramedic naloxone despite increasing annual overdose

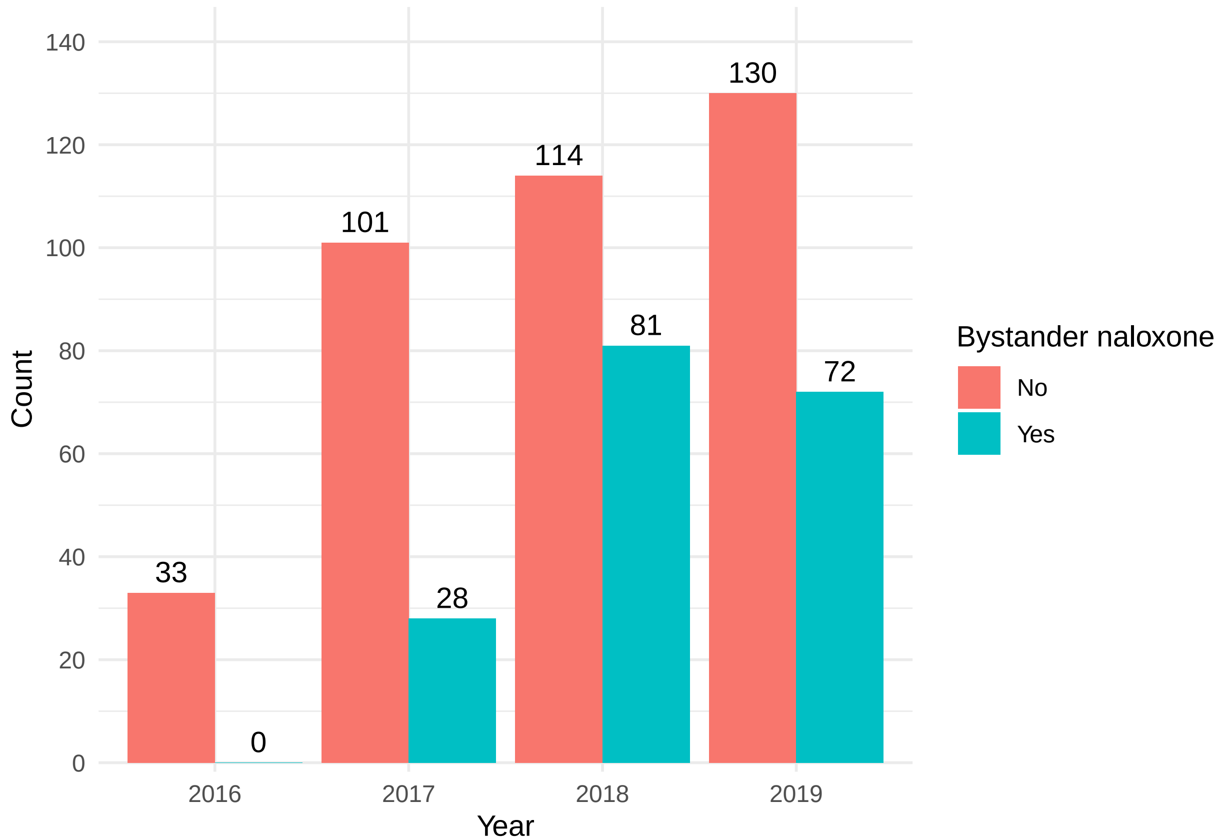

Figure 3.2. Counts of cases with and without bystander naloxone for 2016-2019, indicating an increasing rate of nalaxone PTA

numbers. This is contrary to previous findings which found that the proportion of cases with paramedic naloxone tended to increase with the total number of overdose cases [45], [63].

While the age and sex of the those patients who did and did not receive paramedic naloxone were similar for this study and are consistent with provincially reported averages for this region [55], [56], the small percentage of the population it captured and the decreasing proportion of overdoses it captures are concerning, and the generalization of paramedic naloxone as a metric seems suspect.

One possible reason for the overall low capture rate of paramedic naloxone is the Ontario clinical requirement of an inability to ventilate patients, as previous work has found that paramedic services who have clinical requirements for respiratory effort or ventilation saw lower paramedic naloxone rates [63]. This brings up the important consideration that the effectiveness of paramedic naloxone as a metric (and the generalization of these results to other paramedic systems) is directly linked to the local EMS protocol for the use of naloxone. As an example, Merchant *et al.* [66] found that in Rhode Island EMS records, naloxone over-represented overdoses likely due to its use in a diagnostic fashion as part of an "impaired consciousness" protocol where naloxone was the "last on a sequential list of interventions that crew members may carry out for patients with impaired consciousness." Similar results were found in Maryland [65] and other centers [70]. Comparatively, these findings indicate that paramedic naloxone underrepresented the problem, likely due to a more restrictive provincial medical directive requiring both suspected opioid overdose and an inability to ventilate patients effectively.

In our analysis of opioid overdose location type, a larger proportion of cases occurring in a home received paramedic naloxone, as compared to calls in public places which were more likely to receive bystander naloxone. This difference is likely the result of multiple factors. The increased rate of paramedic naloxone in homes may be related to the operational complication of ventilating patients while extricating them from small and crowded houses. In these cases, the patient is often ventilated in situ while naloxone is titrated to restore a patient's ventilatory drive and then extricated. This is opposed to the larger and more accessible public places which are commonly stretcher accessible, thus negating some of the operational necessity for naloxone. The negative association with public places may also relate to the type of public places where opioid overdoses were occurring. In many cases, these public places were facilities like community outreach centers and homeless shelters that serve marginalized populations and are locations which distribute naloxone kits or where citizens are more likely to carry naloxone kits. The association between paramedic naloxone and call location suggests that in addition to only capturing a small portion of opioid calls, paramedic naloxone does not capture the more marginalized sectors of society, while over-representing those who are able to obtain stable housing, thus further affecting the validity of paramedic naloxone as a metric. While many previous studies have used paramedic data for geo-spatial explorations, this appears to be the first examination of call location type in relation to paramedic naloxone administration.

In conversation with frontline paramedics, it was also anecdotally theorized that heavier patients would be more commonly administered naloxone due to the difficulty of lifting and moving large patients when they are unconscious, as well as complications of airway management and manual ventilation of larger patients. However, in this study, we found no statistical difference in the weight of those patients who did and did not receive paramedic naloxone (p: 0.25) indicating that, at least for this population, patient weight does not seem to have a significant impact on paramedic naloxone utility as a metric.

The decreasing proportion of overdoses captured by paramedic naloxone is also an important consideration in paramedic naloxone's utility as a metric. While paramedic naloxone captured 31% of overdoses in 2017, 2019 showed only a 14% capture rate.

The significant increase in bystander naloxone is highly likely to be related to the decrease in paramedic naloxone, as total overdose rates continued to rise. While previous studies have found the bystander naloxone was associated with a house/residence, these studies had examined significantly different populations from our sample [71], [72].

In Ontario, aggressive marketing campaigns by public health agencies along with major increases in availability have led to exponential growth in the distribution of community naloxone kits, going from just 83 kits being distributed in 2016 to 4089 kits in 2019 in Peterborough County/City alone. This program growth has also seen a corresponding increase in bystander naloxone being documented by paramedics (21% in 2017, versus 36% in 2019). This growth implies that bystanders, who are often friends and family of the patient [73], are becoming de-facto first responders to these events, reducing the need for paramedic treatment with naloxone [69], [71]. While Ontario paramedics are not prevented from giving naloxone to someone who has received bystander naloxone [74] it is rarely necessary [69], and occurred in only 2% of cases in this study. This shift in naloxone provider away from paramedics indicates that paramedic naloxone rates are not sensitive to policy changes/new programs and thus further reduces paramedic naloxone's usefulness as a metric.

The decreasing proportion of opioid overdoses captured with paramedic naloxone from year to year is also particularly concerning as this violates the remaining two requirements for a public health metric, namely to be stable over time and to detect changes over time. In this case, an agency relying on paramedic naloxone as their metric to monitor community overdoses would see a significant “improvement” in their overdose numbers, when in fact their community overdose situation was deteriorating without their knowledge.

Despite paramedic naloxone’s shortcomings as a standalone metric, it is important to consider the use of our data within a larger system. Paramedic naloxone does have a function as a secondary marker within a larger metric encompassing paramedic determination (as was done here) to help capture those cases which may be mis-coded. A sudden change in the proportion of total overdoses who receive paramedic naloxone may also be an important indicator of changes in the local drug market. A sudden increase in paramedic naloxone proportion could indicate a sudden increase in the potency or contamination of the local drug supply as people who use drugs are not able to manage overdoses at home and turn to emergency services for support. Resuscitation with naloxone by a paramedic has also been associated with an increased risk of drug-related and all-cause mortality in follow-up studies [75], [76], while repeated resuscitations with naloxone by a paramedic were associated with a two-fold increase in the risk of drug-related mortality [76]. In this case, patients receiving naloxone from a paramedic, especial if it occurs on more then one occasion, may be candidates for a more targeted harm reduction interventions.

On the other hand, decreases in the proportion of cases where paramedics give naloxone may be an indication of increased effectiveness of community harm reduction programs or other local initiatives. A change either way may also be indicative of changes in the relationship between the people who use drugs community and local emergency services.

Further study would be needed to examine the full potential of paramedic naloxone administration rates within a larger metric.

3.3.1 Limitation to approach

This approach to developing metrics relies on paramedics to identify and correctly code overdoses. While one of the main duties of a paramedic is to rapidly identify the cause of a patient's illness or injury, the lack of a data dictionary for the ACR again presents a problem as there are several very reasonable alternatives that could be documented for the prototypical opioid overdose patient (i.e., unconscious, apnea, alcohol/drug intoxication). While some correction for this is made by adding all cases where a paramedic gave naloxone to the dataset (by Ontario protocol if naloxone is given, the paramedic believes the case is an opioid overdose), some opioid overdoses are still likely to be miscoded. However, it is more likely that opioid overdoses are under-represented in coding rather than over-represented. In an internal quality assurance review by PCCP, very few cases documented as opioid overdoses by paramedics did not meet the Canadian Institute for Health Information (CIHI) direction for ICD coding of opioid overdose [77], while multiple cases that did meet the CIHI direction were coded as something else. In this analysis 50 cases of bystander administered bystander naloxone were not documented with an opioid overdose problem code but were instead coded as a generic "Drug and Alcohol intoxication." It is likely that a portion of these 50 "Drug and Alcohol" overdose cases are in fact opioid overdoses that were miscoded. If true, this further reduces the effectiveness of paramedic naloxone as a community overdose metric as our total case count increases, thus further reducing the proportion of opioid overdoses captured using paramedic naloxone.

The use of de-identified data makes it impossible to determine to what extent some individual patients may be repeat patients and what effect these patients may have on the independence of sampling. While we cannot confirm via the data that there are repeat patients, as the author of this thesis is a paramedic working in PCCP's system it is known that more than one patient is represented in this study multiple times. This does imply that the individual observations in the sample are not independent, but at the level of comparison being done, we do not believe this significantly impacts the findings.

This study is of a relatively small sample size in a medium-sized community which may affect its generalizability. Despite Peterborough having the highest per-capita opioid death rate in Ontario during portions of this study [55], opioid overdoses make up only 0.8% of the total call volume.

Another important consideration when working with paramedic data is system evolution. It is important to consider that paramedic systems are always evolving in line with the best evidence-based practices. This can include the addition, modification, or removal of treatment modalities, changing deployment plans, or policy changes in response to developing crises or current trends. For the purposes of this metrics examination, there was only one substantive change to the Ontario naloxone medical directive during the study period. In July 2017, the minimum age for administration of naloxone by a paramedic under the medical directive was lowered from $\geq$

18 to $\geq$ 12 years. Only 3 of the opioid overdose cases were $<$ 18 years old and all 3 cases occurred after the in-force date of the directive change, making it unlikely for the change to have affected these results.

3.4 Conclusion

In this chapter, we have shown that paramedic naloxone, when used as a standalone metric, fails to meet the criteria of a good public health metric and as such is an ineffective metric for community opioid overdoses when used in isolation. It was also shown that bystander naloxone has an inverse relationship to paramedic naloxone, but more study is needed to determine what role bystander naloxone and paramedic naloxone may have as components of a larger system of metrics. This chapter has also shown the importance of a thorough understanding of the individual elements of paramedic datum as well as the interconnectedness of these data points. In reality, it is very likely that very few paramedic data points can be extracted as a simple count and immediately used as a metric but instead will need to be modelled within the context of multiple contributing factors.

Chapter 4

Temporal Distributions - The Importance of Time

In Chapter 3, we discuss the important considerations when determining what data points will be used to select data of interest. Now that we have a valid pool of cases to examine, let's look at what can be done with the data on these cases.

One area of interest is the temporal distribution of pre-hospital call volumes. Like other areas of medicine, paramedicine is affected by seasonality. Deaths due to flu increase in cold months [78] and motor vehicle collisions increase on long weekends [79]. Scheduling and resource deployment must take into account these temporal variations and balance the available resources with the predicted need all while maintaining fiscal responsibility and a strategic reserve to account for predicted surges in call volumes. The impacts of surges and seasonality are also not equal across paramedicine. Take the example of a traffic collision or house fire that generates 4 acutely ill patients. In a large service (i.e., Toronto, York region, Ottawa) that staffs 30 plus vehicles per shift, 4 ambulances to a traffic collision represents less than 10% of their staffing and a minor imposition, but to a smaller service such as Haliburton, which only staffs 3 ambulances at night, this call would almost certainly overwhelm their available resources.

While it is not possible to predict truly random events, the majority of paramedic calls are not actually random but are the result of a confluence of various factors all of which have some level of probability attached to them. By taking these factors into account it should be possible to create models which could predict with a reasonable level of certainty the system needs over a given period of time and help paramedic services deploy resources more efficiently. These models would also help paramedic services when they must justify their requests for additional funding to municipal council/provincial government as a properly built model would take the design of deployment plans away from the realm of “expert opinion” and into the territory of properly backed science.

4.0.1 Supporting our Partners

Temporal models from paramedic data also have the potential to support many other agencies. Paramedics regularly interact with patients who receive support from various healthcare and social assistance agencies. In the process of assessing and treating these patients, paramedics collect a great deal of information that could support these agencies’ operations and improve the service they provide their clients. However, due to privacy laws, sharing specific patient data with partner agencies can be complicated, but the sharing of aggregate data in the form of a temporal model is much easier[1]. One example where paramedic temporal models can benefit a partner agency is in the implementation of syndromic surveillance. Syndromic surveillance is a system of public health monitoring which relies on the real-time influx of data to detect changing trends in patient presentations, as opposed to clinical diagnosis or laboratory tests, to warn public health officials of impending crisis [80].

[1] Assuming appropriate ethical precautions are considered and included.

The use of syndromic surveillance systems for opioid overdoses by public health agencies is becoming increasingly popular [81], [82], however, the choice of data to include in the system can be complicated [82]. In order to be effective, a thorough understanding of the normal ebbs and flows of the system's component values must be obtained to prevent false alarms. While paramedic data is well suited for these types of programs due to its real-time nature and broad patient base, the lack of published baselines has proved problematic and as such the validity of the inclusion of paramedic data into syndromic surveillance systems still needs to be proven.

In addition to surveillance systems, knowing when and where overdoses happen can help agencies target their work in the areas most in need. In fact, the idea for this analysis came from a specific request from Peterborough Public Health (PPH). In 2018, PPH along with other local social service agencies were applying for a permit to open a safe consumption site in the city of Peterborough. As part of the application, hours of operation had to be included. While PPH realized that a standard 9-5 schedule was not practical, they did not know what hours would be optimal. At that time, none of the opioid monitoring data which was being collected (primarily ED and coroner data) was available at a temporal precision below a daily count. After a presentation about my ongoing work exploring paramedic data, PPH requested an analysis of the temporal trends for paramedic calls for opioid and other drug use. This early work would ultimately lead to this thesis.

4.0.2 Previous Work

While a fair amount of research has been conducted on drug use and its trends related to ED visits [83]–[85], less work has examined the temporal trends in paramedic call volume related to drug use.

Several studies have focused on larger epidemiological issues and long-term models [86], [87] but few have included the level of temporal detail below monthly or annual counts [88]. Often temporal trends are described as changes in case counts as part of a time-series or longitudinal study examining other demographics but lack the temporal or statistical accuracy necessary for modelling. Two studies have examined temporal trends for opioid overdoses using paramedic data in detail. In a 2017 Norwegian study examining non-fatal opioid overdoses, Madah-Amiri *et al.* [89] found decreased call volumes in the early morning followed by peak call volumes at 16:00 and 20:00, however they do not report on the statistical significance of these differences. They did find no significant differences in day of the week and a significant increase in overdoses during summer months peaking in August. In a 2006 study of Rhode Island opioid overdoses, Merchant *et al.* [66] found significant cyclical patterns in calls per month (peaks: August/September, trough: December/January) and calls per hour (peak at 21:00, trough at 07:00) and no significant patterns in day of the week or day of the month.

4.1 Methods

4.1.1 Populations

The patient population for this chapter examines the PCCP ePCR dataset from 2017-2019 and was divided into 3 populations:

- Opioid Overdose
- Non-opioid Overdose
- Alcohol intoxication

The opioid overdose population was selected using the criteria described in Chapter 3. The non-opioid overdose and alcohol intoxication populations were extracted by a search of the ePCR database using the appropriate numeric problem code for “Drug Overdose - Non-Opioid (81.3)” and “Alcohol Intoxication (81.2)” respectively. The numeric problem code (ie: 81.3) was chosen over the problem code description (ie: “Drug Overdose - Non-Opioid (81.3)”) as the problem codes have remained consistent over the time frame of interest, while the names have varied slightly.

Data for 2016 was originally included in this analysis but was removed as the non-opioid overdose problem code was not introduced until early 2017.

4.1.2 Analysis

Analysis for trends were examined in the following categories:

- Time of day (defined in 1-hour blocks)
- Day of week (Monday, Tuesday. . .)
- Day of Month (1st, 2nd . . .)
- Month of year (January, February. . .)

Call date and time were determined by the date and time which the call was initially received by the Central Ambulance Communication Center (Call Received Time). Call Received Time was chosen as that is the date/time object which most closely approximates the time of incident and is consistently available. While the ACR does have a time of incident field, it is not a required field and is often not completed.

Table 4.1. P-values for inter-year and overall comparison of alcohol intoxication cases in temporal fields.

	Inter-year	Overall
Month	$p < 0.001$	$p < 0.001$
Day of Month	0.0478	$p < 0.001$
Day of Week	0.3473	$p < 0.001$
Hour	0.3508	$p < 0.001$

Table 4.2. P-values for inter-year and overall comparison of opioid overdose cases in temporal fields.

	Inter-year	Overall
Month	$p < 0.001$	$p < 0.001$
Day of Month	0.5462	0.119
Day of Week	0.8656	0.5939
Hour	0.2509	$p < 0.001$

Statistical analysis for comparison of counts in each temporal field was done using a Chi-square test for goodness-of-fit with a null hypothesis of equality, except in cases where $> 20\%$ of expected counts were less than 5 or where any expected count was less than 1. In these cases, a Fisher Exact Test was used.

Table 4.3. P-values for inter-year and overall comparison of non-opioid overdose cases in temporal fields.

	Inter-year	Overall
Month	$p < 0.001$	$p < 0.001$
Day of Month	0.909	0.7887
Day of Week	0.927	0.7511
Hour	0.8536	$p < 0.001$

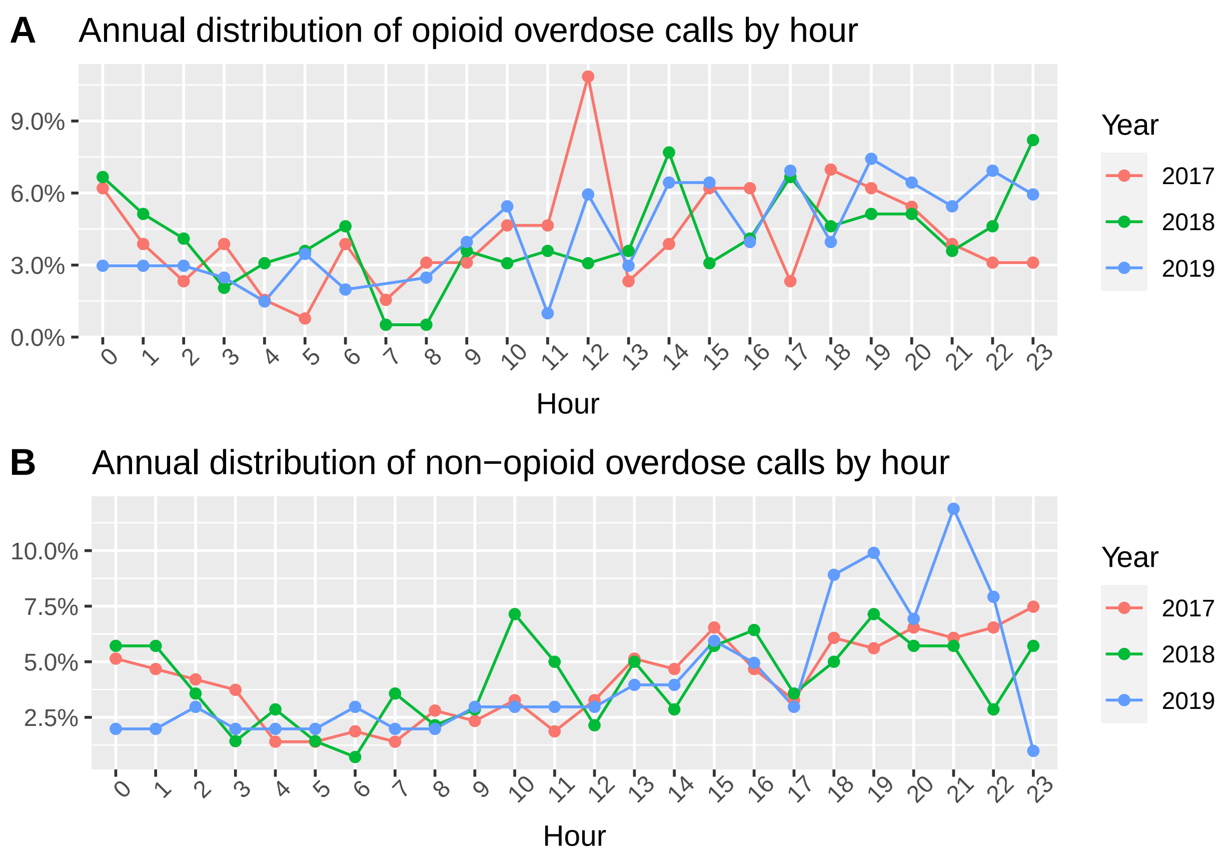

Figure 4.1. Hourly distribution of opioid overdose (A) and non-opioid overdose (B) cases

4.2 Results

4.2.1 Opioids and Non-Opioids

526 opioid overdose cases and 455 non-opioid overdose cases were found between 2017 and 2019. Tables 4.2 and 4.3 list the p-values of the inter-year and overall Chi-square analysis. In both populations, the monthly counts and hourly counts show a significant difference in the overall count, however only hourly did not show a significant difference from year to year. This indicates that only hourly counts have a

sustainable trend over the 3 year study period. This hourly trend shows higher counts in the evening/overnight periods followed by lower counts in the early morning for both populations (Figure 4.1).

4.2.2 Alcohol Intoxication

1539 Alcohol intoxication cases were found between 2017 and 2019. Table 4.1 lists the p values of the inter-year and overall Chi-square analysis. Unlike opioid overdose and non-opioid overdose cases, significant differences were found in all 4 temporal categories for alcohol intoxication cases, with only the monthly and Day-of-Month counts having a significant difference in the year-to-year analysis. This indicates that Day-of-Week and Hourly counts all have stable trends from year to year. Hourly trends show a strong cyclical pattern, starting low in the mid-mornings (0400-0900), increasing slowly over the day to peak at 0100, followed by a rapid decline until 0400. Day-of-week trends show low levels of calls on Monday-Thursday, followed by a slow increase on Friday, to a peak on Saturday and then a decrease on Sunday.

4.3 Discussion

In a review of the different temporal fields in pre-hospital calls, it appears that temporal trends can be detected in prehospital data, but some consideration must be made. The first thing we must consider when examining the temporal nature of paramedic data is that paramedicine is a 24/7 operation. While we as a society have designated that a day ends at midnight and a weekend ends on Sunday, Paramedic calls continue to happen regardless of the end of a day, week, or month. A prime example of this is seen in the day of week field for alcohol intoxication calls (Figure 4.3). The figures

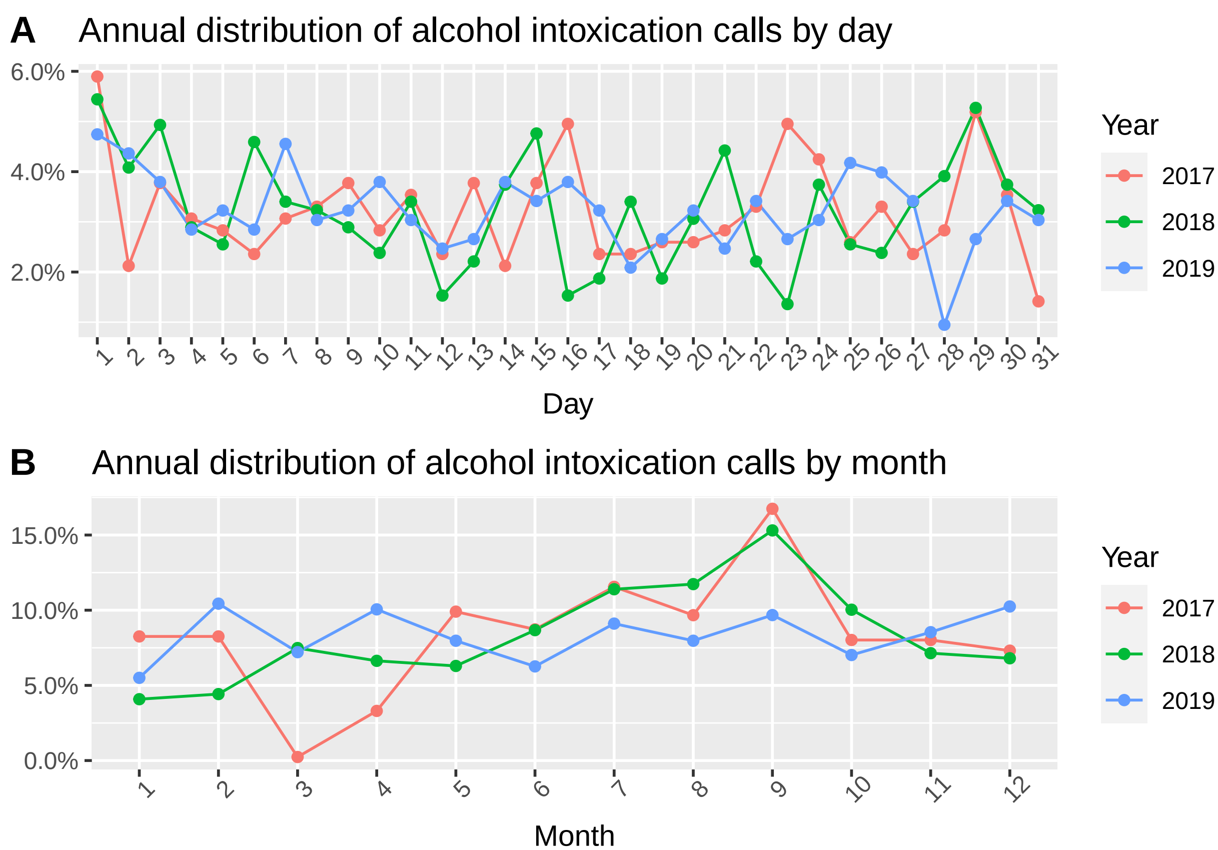

Figure 4.2. Temproal distributions of alcohol intoxication cases across 2 temporal scales: A: Day of Month, B: Month of the year

present a large number of calls on a Sunday, which seems odd for this region. However, when we examine the time of cases on Sunday, 57.5% of cases occur between 00:00 and 04:00. These calls are most likely the result of patients who went out Saturday night and have not returned home yet. This idea is further supported by looking at call times for alcohol intoxication calls throughout the weekend (Friday-Sunday) where most alcohol intoxication cases occur in the 00:00 to 03:00 period. While the idea that Saturday night continues into Sunday morning is not new to anyone who

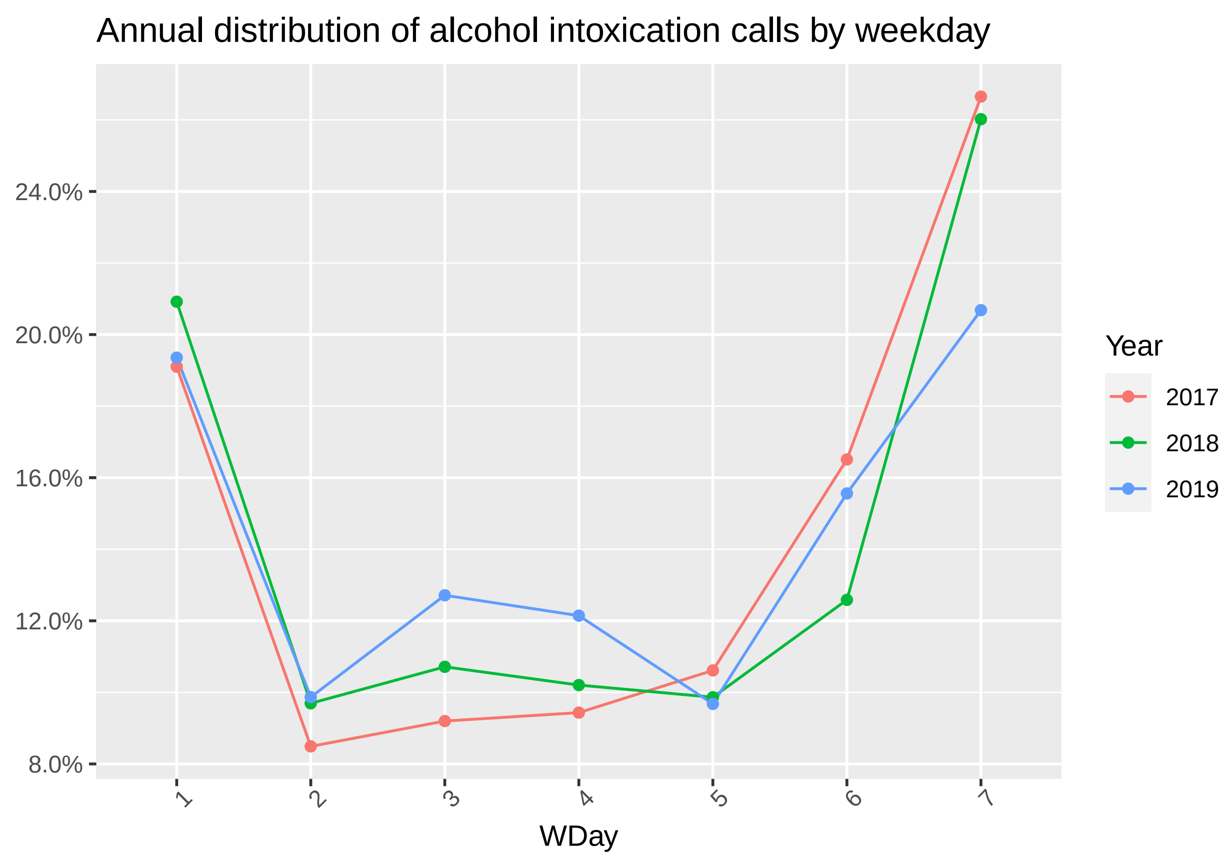

Figure 4.3. Day of week distribution of alcohol intoxication cases

has ever worked in the service industry, it does illustrate an important point. Many paramedic temporal fields will have "bleed-through" from the end of one temporal unit into the next and this bleed-through effect must be considered in any analysis.

4.3.1 Non-opioid Temporal Trends

When viewing the data it is also important that we consider the use of aggregate data versus non-aggregate data. A good example of this is the non-opioid overdose day of month counts. When the data is viewed in aggregate form, as a case count per day over 3 years (Figure 4.4 A), the number of cases appears stable over the month with

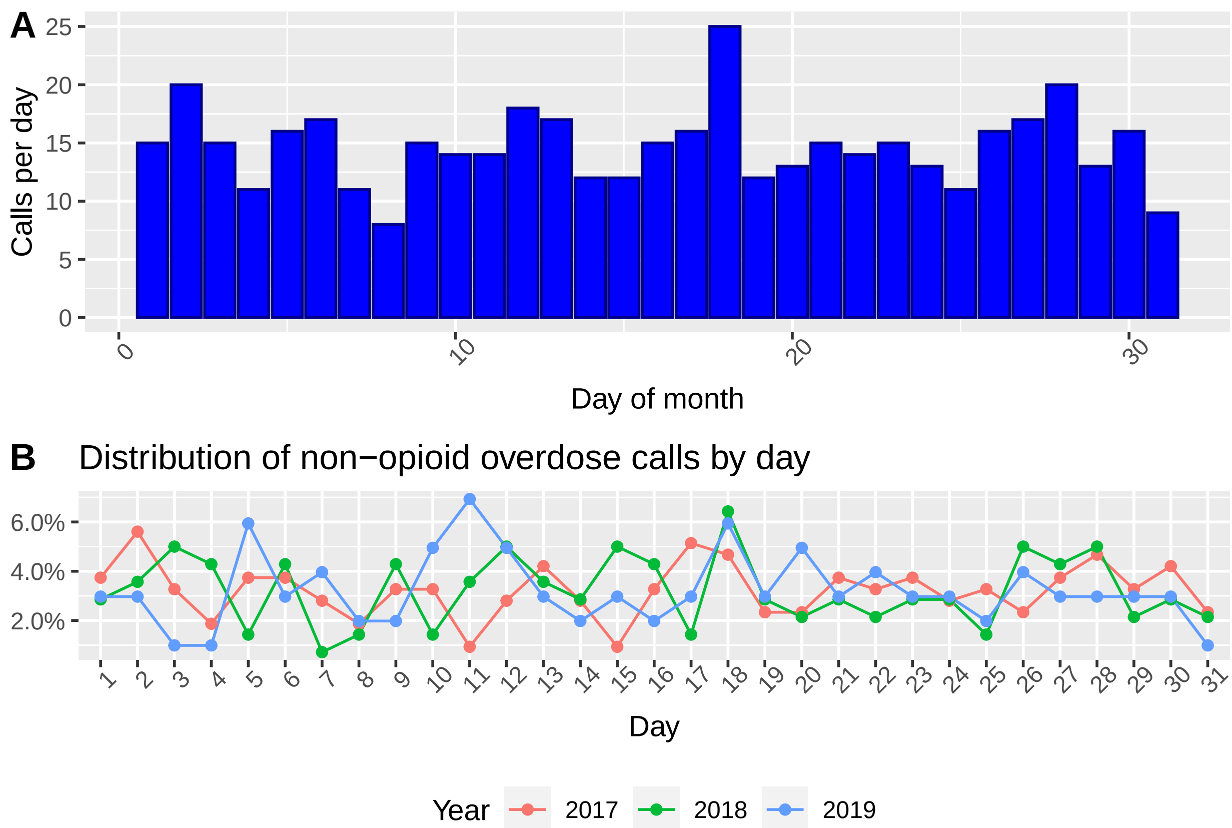

Figure 4.4. Comparison of non-opioid overdose cases as aggregate (A) and non-aggregate annual trends (B)

a few significant peaks and a slightly increasing trend towards the end of the month. However, when the counts a broken down by year, the variability between years is far more obvious (Figure 4.4 B). This is also supported by the Chi-square which shows significant variability between years. Now one possible cause for this could be a poor choice of metric in the non-opioid overdose population. In retrospect, the "Drug Overdose - Non-Opioid (81.3)" problem code is not specific to recreational or addiction-related drug use but instead captures, as the name suggests, all non-opioid-related drug use. This likely includes a large proportion of psychiatric patients who overdosed with the intent of suicide or self-harm. In a post-hoc analysis, 22% of non-opioid overdose cases also included the "Behavioral/Psychiatric" problem code as their primary or secondary problem. While the use of the "Behavioral/Psychiatric" problem code does not necessarily indicate suicidal/self-harm intentions as some illicit drugs can also cause behavioural problems or psychiatric breaks, it does mean it is not possible to differentiate between intentional and accidental drug overdoses without a full manual chart review, which is beyond the scope of this thesis.

One possible solution for this would be the introduction of different problem codes for intentional and accidental overdoses (along with clear definitions of the two) for future versions of the ACR, however, this will not help with retrospective analysis.

4.3.2 Opioid Temporal Trends

With these considerations in mind, we can now discuss the usefulness of paramedic data in determining temporal distributions. While opioid overdoses were found to have significant differences in both month of the year and hour of day, only the hour of day has significance for this analysis as month of year also had significant variability between years, indicating that monthly trends change each year. No previous work has compared monthly case count trends from year to year, so it is unclear if this is a normal or a unique finding. One likely cause of the year-to-year variation in monthly trends is floating-point temporal influences, which are factors that occur on a regular and predictable cyclic pattern but do not necessarily coincide with a recognized temporal scale. Both fixed- and floating-point temporal influences will be discussed further in Chapter 5.

In terms of the hour of day, while the plot does still show some variation between years, there is a very clear trough in the mid-morning period, followed by increases into the early evening through till midnight. While the trough is consistent with the findings of Mahah-Amirir *et al.* [89] in Norway, the high usage times appear to extend much later into the evening. This may be due to Mahah-Amiri's theory that their sampling includes a larger proportion of recreational opium users as opposed to those with addiction issues.

4.3.3 Alcohol Temporal Trends

When examining the temporal aspects in alcohol intoxication cases, trends were found in more temporal fields. Alcohol intoxication cases show statistically significant differences in case counts for all four temporal fields, but only the monthly counts show variation between years, indicating that day of month, day of week and hour of day all have significant temporal trends which are stable from year to year. These trends include increases in alcohol intoxication related cases on weekends and at the end of/beginning of a month. There is also a very significant trend in alcohol intoxication cases in the hour of day field (Figure 4.2 A), with the lowest case counts in the morning and a dramatic peak from 23:00-03:00. Interestingly, these trends coincide with the legal time to sell alcohol in Ontario [90]. While alcohol can legally be sold starting at 09:00, the LCBO and Beer Store do not open until 10:00 which coincides with the slow increases starting at 11:00. The sale of alcohol must be also completed by 02:00 with all signs of alcohol being cleared away by 02:45. This is likely connected to the decrease in alcohol intoxication related calls seen after 03:00 and supports previous findings in Australia [91] and Amsterdam [92] which have shown that alcohol-related

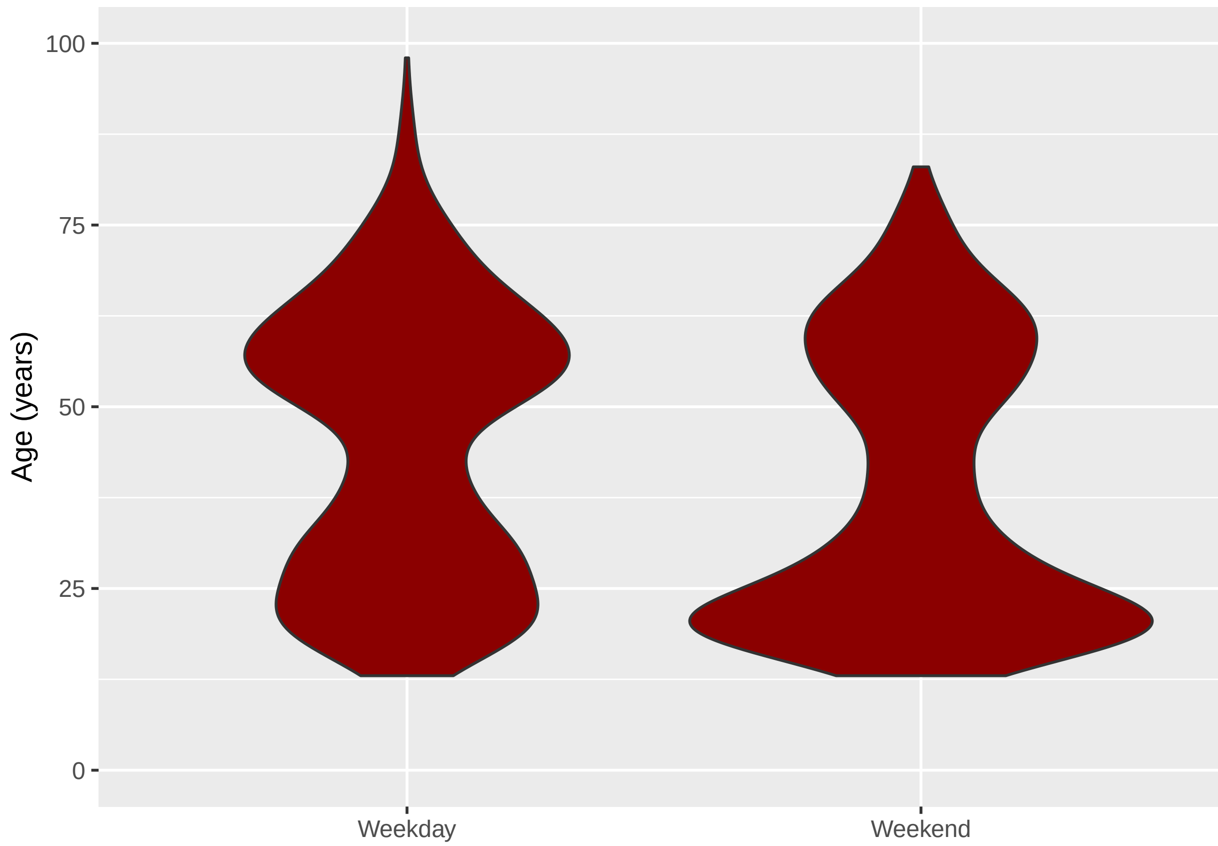

Figure 4.5. Age distribution of alcohol intoxication cases on a weekday vs weekend.

call-outs and injuries are highly related to the legal time where alcohol must stop being served.

This connection between legality and substance use may also be a reason alcohol intoxication has more obvious trends than opioid overdose or non-opioid overdose cases. With alcohol being legal there is less fear of repercussions for calling 911 for a drunk friend than for a friend who is overdosing on illicit drugs. While the *Good Samaritan Drug Overdose Act* provides limited protection for both the caller and the patient [93], many people who use drugs still have fears. There is also a dramatic difference in case counts on weekends versus weekdays and night versus daytime. This brings up a new question of "is there a single alcohol intoxication population?" Previous work has shown that two separate populations in GHB users exist in Helsinki, a weekend/night user population and all other time user populations [94]. In a Fisher Exact comparison of the alcohol intoxication population, there were statistically significant differences in the age distribution of those cases on the weekend (Friday-Sunday) versus those on other days (Monday-Thursday) ($p < 0.001$). As can be seen in Figure 4.5, the weekend alcohol intoxication population tends to be younger, with obvious increases in the 18-25 years of age. Increases are also typically seen in September (5% in 2018 and 2017) (Figure 4.2 B), which is when students return to Peterborough's two large post-secondary institutions from summer break. There was however no difference in the proportion of male to female cases in the weekend vs weekday group (37.16 % vs 34.02, p: 0.227). While the data in this thesis does not allow for further examination, it is possible that the alcohol intoxication population may in fact be two distinct groups, a "weekend party" group and a "weekday drinking" group. Further investigation is needed to determine a viable way to identify and separate these two populations for further analysis. One possible technique could be a geo-spatial analysis examining alcohol intoxication call density in entertainment districts and student housing residences versus other districts. The difference in day-of-week rates may also explain some of the variability in the day-of-month counts. Since weekends do not align with specific days of the month, the increased number of weekend cases may be obscuring smaller trends in monthly case counts. Further investigation is needed to determine if the effects of day-of-week and day-of-month can be separated out.

4.4 Conclusion

While non-opioid overdose and opioid overdose cases do not have a large enough effect to warrant changes in paramedic operation, the variations in temporal trends would be relevant to partner agencies. The small trends noted here are most likely due to the small sample size but could be representative of the large population trends for those people who use drugs. By using these trends, partner agencies will be able to better plan their harm reduction activities for period when they can have maximum impact.

On the other hand, the alcohol intoxication population does have an impact on operations. Prior to Covid, it was not uncommon for PCCP to upstaff some weekend nights to account for the busy entertainment district crowd, who were primarily alcohol intoxication related calls. While in the past, these upstaff calls were typically done on an emergency basis (when service resources were already overwhelmed), if a clearer pattern of alcohol intoxication cases could be determined to account for different causative factors it may be possible to pre-schedule upstaffing, thus taking stress off the service and helping prevent resource depletion.

More work is required to determine the extent to which temporal trends determined from paramedic data can be incorporated into operational planning and support of partner agencies. The trends found here still have significant variation which is not explained by temporal models alone. Through further exploration, it should be possible to find other causative factors which have influenced these temporal trends similar to the influences temporal restrictions on the sale of alcohol have had. Once these factors are identified and incorporated into a model, the ability to use paramedic data for deployment planning and other programming will be greatly improved.

Chapter 5

Point Temporal Impacts

While the overall flow of paramedic call volumes is relatively stable over time, most paramedics will tell you that certain times of the month and certain days of the year are busier. Some of this is superstition and some is due to hard-won experience. The problem with modelling these ebbs and flows of cases is that they are not necessarily at a fixed time point and can be floating temporal points that follow a schedule all their own. The impacts of fixed and floating temporal points are an important consideration of temporal modelling in paramedic data. As discussed in Chapter 4, previous work has shown that certain types of call volumes are impacted by the date or time of year. Motor vehicle collisions increase on long weekends [79]; hot summer days and flu season lead to increased respiratory and cardiac calls [78], [95], [96], but many other time points are not as well quantified.

5.0.1 Social Assistance Payments

One area of temporal trends that has been examined with some depth is the "Cheque Effect" or "Cheque Day Effect." The cheque effect is a common, but not politically correct, description of the temporal association between the distribution of social assistance payments and increases in drug/alcohol-related calls. Previous work in the USA has shown both an increase in overdose fatalities in the 5 days after social assistance distribution as well as relatively higher fatality rates in census blocks with higher numbers of social assistance recipients during the same time frame [88]. Canadian studies have found that the number of users at a British Columbia safe injection site increased significantly in the three days following social assistance distribution [97] as well as an increase in overdose admissions in the three days following social assistance distribution [98]. While no clear causation has been determined, it has been suggested that a sudden influx of cash may be a cue for increased drug consumption [99]. Interestingly, only one study appears to have examined temporal influences of social assistance distribution from a Canadian pre-hospital perspective. In a 1997 study, Verheul *et al.* [100] found statistically significant increases in police and ambulance activity as well as drug-related coroner deaths in the week after social assistance distribution. While they also found an increase in ER visits, it was not statistically significant.

Three social assistance payments were chosen for this analysis.

- **Ontario Works (OW)** is the Ontario provincial government social assistance program for those who are in financial need and unemployed. [1].
- The **Ontario Disability Support Program (ODSP)** is the Ontario provincial government social assistance program for those residents in financial need who are unemployed or underemployed due to a disability (as defined by the ODSP Act of 1997), or those who meet the definition of a "Prescribed Case" as defined by the Ontario Ministry of Children, Community and Social Services

[1]. Financial need for OW and ODSP is defined as a household which does not have sufficient financial resources to meet basic living expenses [1]. Both OW and ODSP payments are distributed on the last business day of the month [1].

- The **Canadian Child Benefit (CCB)** is a tax-free Canadian federal government payment to support eligible families with the costs of raising children. Payments are distributed monthly on the 20th of each month (or the last business day prior to the 20th), with the exception of December, where the payment is made on the 13th of the month (or the last business day before the 13th) [101].

5.0.2 Full Moon

The full moon has had a long history of superstition associated with its appearance. One common superstition in first responders is that during a full moon psychiatric and drug-related calls or calls with "weird" incident histories are more common. This idea was originally included more as a joke at the request of **many** paramedic and nurse co-workers, but a review of previous research has revealed some "lunar effects."

Two separate studies in 1996 and 1979 found that there were no significant differences in hospital admission [102] or police and fire service call volumes [103] related to lunar phases. However, Onozuka *et al.* [104] did find a statistically significant increase in emergency transports due to traffic collisions on full moon nights compared to other nights (relative risk 1.042, CI: 1.021-1.063) in Japan.

The purpose of this chapter will be to examine OW, ODSP, CCB distribution dates for any changes in paramedic call volumes in the days following distribution. The periods following the full moon will also be similarly examined.

5.1 Methods

5.1.1 Populations

This analysis uses the same population as described in section 4.1.1, examining the three-year aggregate day of month distributions for opioid overdose, non-opioid overdose, and alcohol intoxication cases. An additional non-intoxication population has also been added as a control to ensure any findings are related to the population of interest and not a systemic influence. The non-intoxication population was selected by removing all cases from the opioid overdose, non-opioid overdose and alcohol intoxication sub-populations from the main population resulting in an "everyone else" group.

Dates for Canadian Child Benefit (CCB) for 2018 and 2019 were obtained from the Canadian Revenue Agency website [101]. Payment dates for 2016 and 2017 were determined based on published payment dates for 2018 and 2019. A request was made to CRA to confirm payment dates for 2016 and 2017, but no response was received.

OW and ODSP payment dates were provided by the City of Peterborough Social Services Department, the municipal agency responsible for administration and distribution of OW and ODSP benefits for the City and County of Peterborough under a City/County shared services agreement.

Dates for the full moon for the city of Peterborough were obtained from www.timeanddate.com..[1]

[1] Full URL: `https://www.timeanddate.com/moon/phases/canada/peterborough?year=2016`

5.1.2 Analysis

Analysis of the temporal influences of social assistance payments was completed using the proportion of total calls for the population of interest, in a 1-, 3- and 5-day period after payment (Lag) compared to the proportion in a corresponding 1-, 3- and 5-day period prior to payment (Pre).

Since this analysis compares case volumes by proximity to payment dates, and ODSP and OW are paid on the same day, it is not possible to differentiate between ODSP and OW recipients. For the purposes of this analysis, OW and ODSP have been combined into a single point temporal influence (OW/ODSP).

The full moon analysis consisted of a comparison of the proportion of calls on the full moon, versus the day after (Lag) and the day before (Pre) as well as a comparison against the day of the new moon. A second comparison was done for the "week of the full moon" which compared the proportion of calls on the day of the full moon +/-2 days to the day of the new moon +/- 2 days.[2]

The date of the new moon was determined by subtracting half of a lunar cycle (14 days) from the date of the full moon. Analysis was completed using a two proportion Z-test comparing the proportion of cases of the corresponding Pre/Lag against the total case count, under the hypothesis

$$H_0 : \hat{p}_{Lag} \leq \hat{p}_{Pre} \qquad H_a : \hat{p}_{Lag} > \hat{p}_{Pre}$$

[2]The number of conversations this topic started with co-workers was very extensive and the variety of superstitions was rather impressive. While I realize this is kind of silly for a formal thesis, it was actually very interesting to my co-workers. I also **really** wanted to kill this myth.

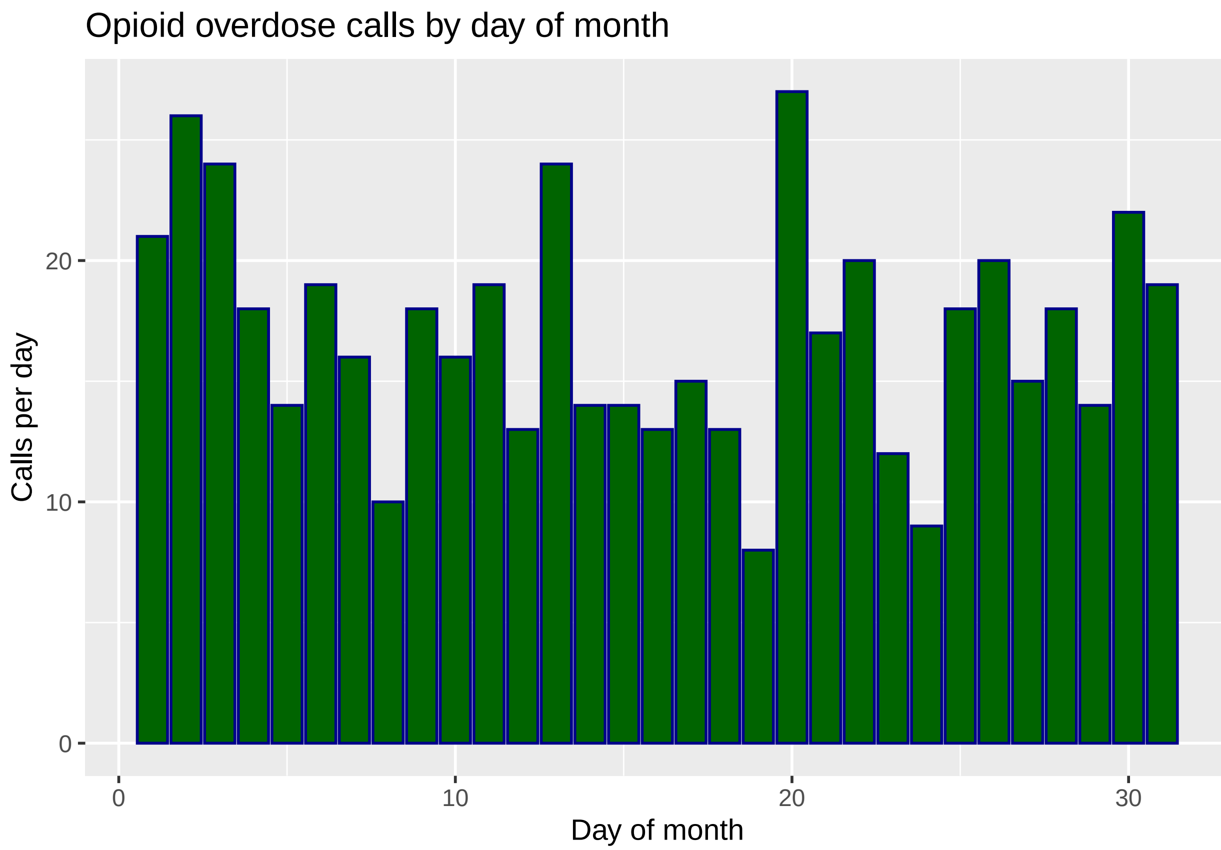

Figure 5.1. Aggregate day of month distribution for opioid overdose calls from 2017-2019

Proportions of calls that occurred within each Pre and Lag period were determined for each sub-population based on the example here:

$$\hat{p}_{\text{Lag1}} = \frac{n_{\text{Lag1}}}{N}$$

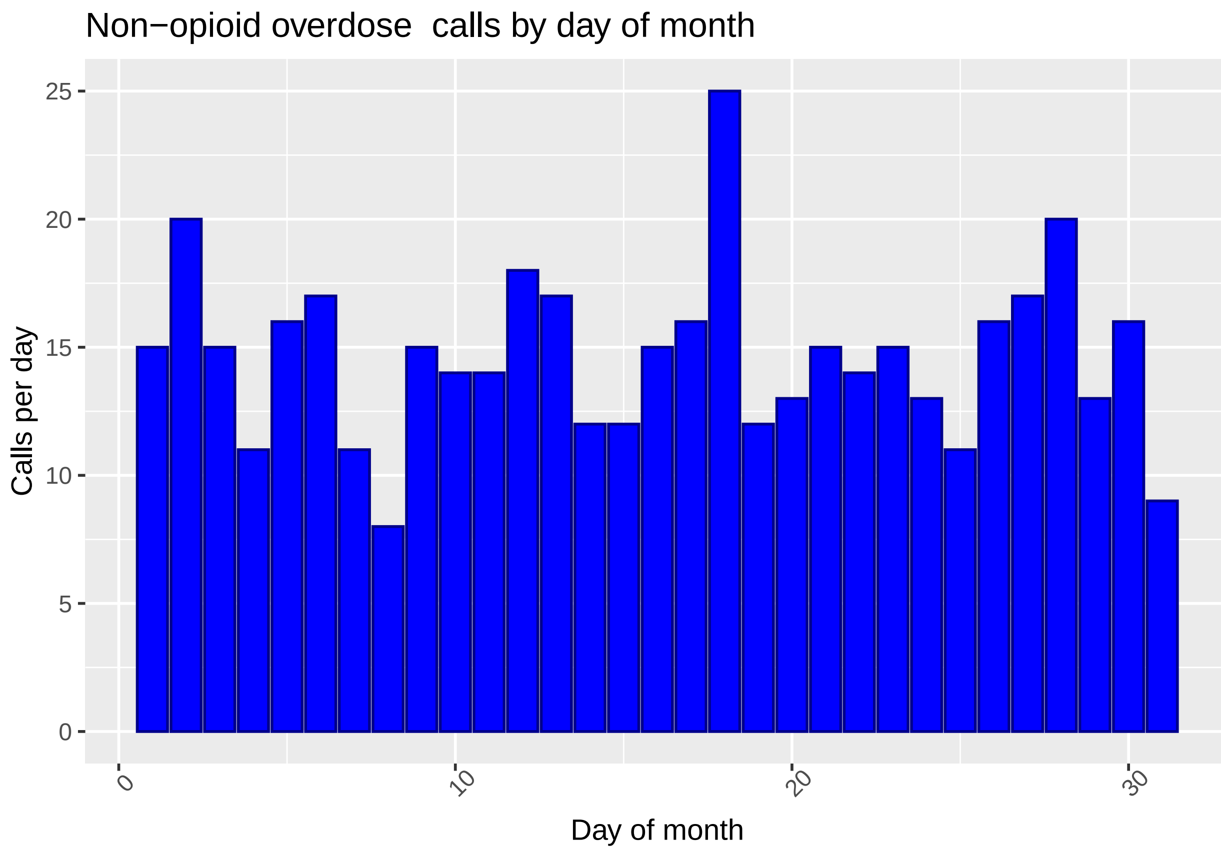

Figure 5.2. Aggregate day of month distribution for non-opioid overdose calls from 2017-2019

Post-hoc analysis

While most analyses are planned in advance, sometimes the questions do not appear until the investigation begins. This was the case with temporal the exploration of temporal distribution. When examining the aggregate distributions of opioid overdose and non-opioid overdose calls for day of the month (i.e., aggregate version of Figure 4.1), it was noted that a few specific days appeared to have larger counts than adjacent days causing an apparent spike. These are seen as the 13th and 20th in the opioid overdose distribution (Figure 5.1) and the 18th in the non-opioid overdose Distribution (Figure 5.2). While visually the counts on the 13th, 18th and 20th appear

Table 5.1. Proportion of opioid overdose calls in the Pre and Lag periods of OW/ODSP with corresponding p-values of proportion test.

	Pre	Lag	P Value
1 Day	0.0247	0.0532	0.0129
3 Day	0.0760	0.1464	$p < 0.001$
5 Day	0.1464	0.2110	0.004

Table 5.2. Proportion of alcohol intoxication calls in the Pre and Lag periods of OW/ODPS with corresponding p-values of proportion test

	Pre	Lag	P Value
1 Day	0.0292	0.0604	$p < 0.001$
3 Day	0.0910	0.1494	$p < 0.001$
5 Day	0.1592	0.2112	$p < 0.001$
7 day	0.2183	0.2664	0.0011

different, a two-proportion Z-test examining the number of calls on each day of interest (as a proportion of the total calls in the population) were performed to confirm a significant difference in case counts did exist between the day of interest and the day before and the day after. Once the spike was determined to be significant, the question then became if the increase was the result of a single day large scale event which led to an increased case count on one day or if the increases were the result of repeated small increases which would be indicative of a point temporal influence occurring across multiple months. This was determined by examining the proportion of cases on each individual instances of the date in question (i.e., the case count for January 20, 2017 and February 20, 2017... December 20, 2019).

$$H_0 : \hat{p}_{Spike} \leq \hat{p}_{Pre/Post} \qquad\qquad H_a : \hat{p}_{Spike} > \hat{p}_{Pre/Post}$$

Table 5.3. Proportion of non-intoxication cases in the Pre and Lag periods of OW/ODPS with corresponding p-values of proportion test.

	Pre	Lag	P Value
1 Day	0.0325	0.0342	0.0594
3 Day	0.0985	0.1019	0.0365
5 Day	0.1624	0.1691	0.0019

Table 5.4. Proportion of opioid overdose calls in the Pre and Lag periods of CCB with corresponding p-values of proportion test

	Pre	Lag	P Value
1 Day	0.0266	0.0247	0.5000
3 Day	0.0741	0.0817	0.3650
5 Day	0.1350	0.1312	0.5362

5.2 Results

For the OW/ODSP comparison, both opioid overdose and alcohol intoxication populations showed a statistically significant ($p < 0.03$) increase in calls in the 1, 3, and 5 day period after OW/ODSP payments were distributed (Table 5.1 & 5.2) while the NonIntox population showed a statistically significant increase in the Lag3 and Lag5 periods, but not in Lag1 (Table 5.3). The non-opioid overdose populations showed no significant increase. For CCB comparisons, only alcohol intoxication cases showed a statistically significant ($p < 0.01$) increase in the proportion of calls in the period after CCB payments were distributed and only in the 1 and 3 day lag period. No other comparison was significantly different.

Table 5.5. Proportion of alcohol intoxication cases in the Pre and Lag periods of CCB with corresponding p-values of proportion test.

	Pre	Lag	P Value
1 Day	0.0208	0.0357	0.0084
3 Day	0.0695	0.0981	0.0026
5 Day	0.1475	0.1644	0.1071

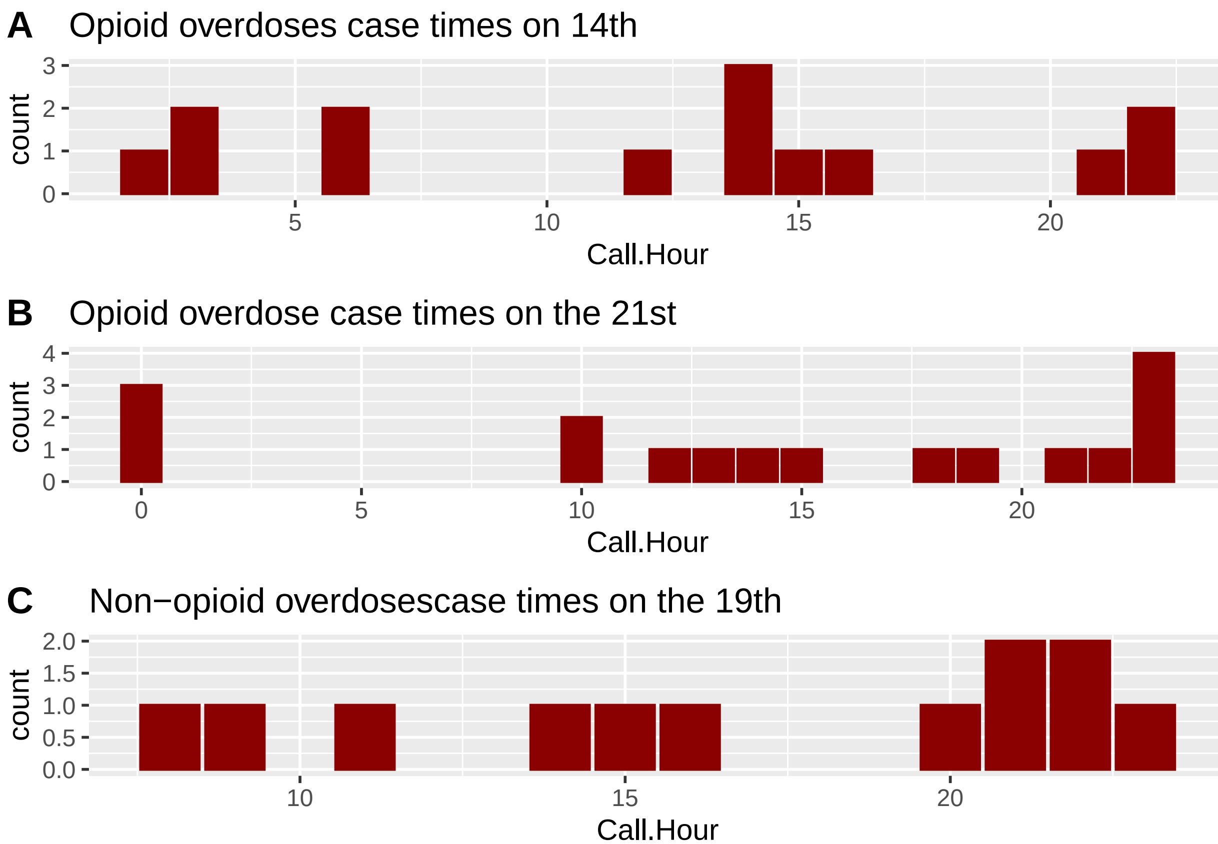

Figure 5.3. Plot examining the time of day for cases on the day after a spike day. Graphics show that majority of cases do not occur just after OO:OO and as such are not bleed through from the previous night.

For the Full moon, no significant differences were found in the proportion of calls in any temporal comparisons.

5.2.1 Spike date: Post-hoc analysis

In the post-hoc analysis comparing the spike days to the preceding and following day, calls on the spike day were found to be significantly higher than the preceding day ($p < 0.05$), but not significantly different from the day after. Initially, the lack of difference between the spike day and the post day was thought to be due to bleed through in

Table 5.6. Comparison of opioid overdoses on the 13th day of the month with the previous and following days.

	12th	13th	14th
Total cases per date	13	24	14
Max cases per single date	2	2	2
Max Percent per single date	15.4	8.3	14.3
p-value of Comparison	0.0471		0.0685

Table 5.7. Comparison of opioid overdoses on the 20th day of the month with the previous and following days.

	19th	20th	21th
Total cases per date	8	27	17
Max cases per single date	1	3	4
Max Percent per single date	12.5	11.1	23.5
p-value of comparison	$p < 0.001$		0.0829

late night/early morning calls from the spike day, however in examining the hour of calls in the day after, <25% of cases occurred before 05:00 in any of the post days which makes bleed through unlikely (Figure 5.3). The analysis examining the single date spike versus the ongoing peak usage trend found that no single calendar date represented more than 12.5% of calls for that day of the month, while the pre and post days represented from 8.0% to 23.5% of calls on their respective dates (Tables 5.6, 5.7, 5.8). This indicates that for all three dates the increased case count is due to an overall increased usage (a peak) on that date and not due to one or two days with

Table 5.8. Comparison of non-opioid overdoses on the 18th day of the month with the previous and following days.

	17th	18th	19th
Total cases per date	16	25	12
Max cases per single date	3	2	2
Max Percent per single date	18.8	8	16.7
p-value of comparison	0.022		0.1005

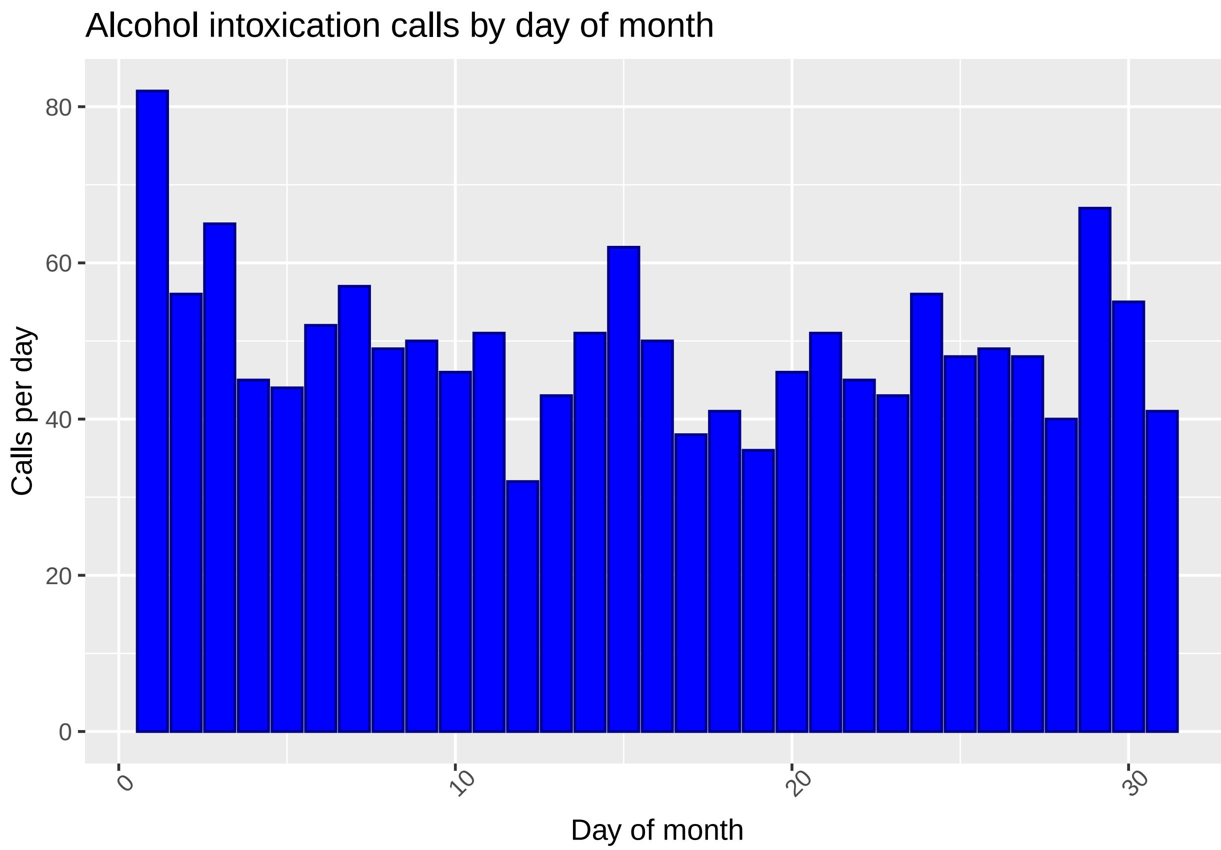

Figure 5.4. Alcohol intoxication calls plotted by day of the month.

an excess of calls (a spike). It is interesting to note that the peak days are not the same within the two populations indicating that the driving factor of these peaks is unique to each population. It is also interesting to note that there are not obviously apparent peak days in the alcohol intoxication population (Figure 5.4). While there are apparent increases on the 15th and 29th, those are both part of trends in the distributions and do not stand out alone like those in the non-opioid overdose and opioid overdoses populations.

In an effort to identify these factors, I spoke with the PCCP paramedic assigned to the Mobile Support Overdose Reduction Team, which is an interdisciplinary team that works directly with and supports people who use drugs. By asking the members of the team with lived experience, their team was immediately able to identify the 20th as the day of CCB distribution. While the 20th peak in the opioid overdose population does coincide with the normal date for CCB distribution, a comparison between CCB distributions and opioid overdose call volumes did not show a significant correlation (Lag0 vs Pre1: 0.032 vs 0.027, p: 0.3577). In addition, only 14 of the 27 opioid overdose cases on the 20th actually occur on a CCB distribution date (remembering that CCB distribution dates vary slightly due to weekends and Christmas). With only 52% of cases on the 20th being associated with CCB distribution, it would indicate that this peak is not solely the result of CCB. However, the fact that those with lived experience with opioids were immediately able to identify the association indicates that CCB may be a contributing factor to an increase in calls on that date. A further discussion with an expanded lived experience panel would likely identify factors related to the 13th and 18th as well, however that process was not within the scope or ethics approval of this thesis.

5.3 Discussion

While the examination of point temporal influences did find some correlation with drug and alcohol-related calls, other point temporal influences had no correlation.

5.3.1 Full Moon

The lack of association between the full moon and any of the patient populations was not surprising. While Onozuka *et al.* [104] found a statistically significant increase in transport due to traffic-related collisions on full moon nights, the actual difference in daily cases between the full moon and control nights was only 16.3 cases across 4 years for the entire country of Japan, (population 127 million at the time of the study) which would have limited operational significance. Furthermore, they hypothesize the increased transports was due to "increased emotions among older people" due to the lunar cycle leading "to momentary distraction in older people" thus causing increased traffic collisions. Our results do not support such a finding. If this were true, we should see an increase in the non-intoxication population, which includes psychiatric calls, during the full moon. While Onozuka did attempt to control for the confounding variable of weather they used only a single weather station in each prefecture, which range in size from ~ 1800 to ~ 83000 km^2. It seems unlikely that a single weather station could accurately capture the climatological detail necessary for predicting road conditions in an area that large. It is also highly possible that other confounding floating temporal influences aligned with the full moons more often than the control dates thus leading to a spurious increase on full moon dates. This further supports the importance of a proper understanding of environmental and temporal influences in pre-hospital data for inclusions in these models.

5.3.2 OW/ODSP

The increase in opioid overdose and alcohol intoxication related calls in the days following OW/ODSP payments supports previous work on the influences of the "cheque day" effect. While the 2.9% increase in opioid overdose related calls is not likely to impact paramedic operations since opioid overdose cases represent such a small portion of paramedic call volumes, these finding would suggest that support and social service agencies should be prepared for increased usage of their programming in the days after social assistance is distributed. It is important to remember that the opioid overdose cases reported here are only a metric for overall opioid population and represent trends in usage. As such, these agencies should be prepared for an ˜2.9% increase in overall usage of their services, not just a increase from those clients who are more likely to call 911.

The association of non-intoxication calls with OW/ODSP payments is interesting and was not expected. Previous research has not found a "cheque day" effect with non-intoxication calls. The relatively small 0.3% increase in cases post-OW/ODSP distribution may indicate it is not a general increase in call volumes but an increase in a small subset of the non-intoxication population. In an effort to identify this sub-population a post-hoc analysis was run on the non-intoxication population.

For the post-hoc, all patients with the generic "Drug/Alcohol intoxication" problem code (n= 420) were removed from the non-intoxication population and the Lag3/Pre3 and Lag5/Pre5 proportion tests were rerun. No significant increase in the Lag3 time period was found (p: 0.0687), however a small but statistically significant increase in the Lag5 time period remained. Due to its small size, the operational impact of the increase would likely be minimal (˜1.7 calls per day over the 5 day

Lag period), but it does present an interesting research question not previously explored. It is possible that further post-hoc analysis would find other associations between some of the less common call types and OW/ODSP, however, that investigation would have to be carefully structured to avoid the complications of multiple comparisons and the increased risk on incorrectly rejecting a true H_0.

There is also the problem that “Drug/Alcohol intoxication” cases were in the non-intoxication population in the first place. While it is obvious that a group of cases with “intoxication” in the description do not belong in the non-intoxication population, this problem flows back to the complex nature of paramedic data. To sort these cases into their correct sub-categories, a manual review of the individual PCRs would be needed which is not practical and is more ethically complicated as that could lead to the identification of patients. These patients represent only 0.008% of the non-intoxication cases and should have minimal impact for most analysis, as long as their inclusion is considered in the interpretation of the results.

The fact that no relationship was found between non-opioid overdose cases and OW/ODSP payment date may again be due to the mixed composition of the non-opioid overdose population presented in Section 4.3.1. While previous work has shown that those who use non-opioids for recreational/addiction-related uses are more likely to use after social assistance distribution [99], a literature search found no previous associations between social assistance and self-harm/suicidal drug overdoses. As such the mixed nature of the non-opioid overdose sub-population may be obscuring any relationship if one exists.

It is also important to note that OW and ODSP are different programs designed to support different populations of people. For this analysis, the programs have been combined as their payment dates coincide, meaning the impacts of the two populations cannot be separated with the data available in this analysis. As such, no conclusions can be drawn for one population without also including the other. Further analysis might be possible with access to billing data from Peterborough Social Services[3], however accessing that data would be very ethically complicated.

5.3.3 CCB

While the increase in alcohol intoxication cases in the days following CCB distribution matches the accepted theory of the "cheque day" effect, the lack of a statistical relationship between opioid overdose cases and CCB is interesting. This may indicate a difference in the proportion of patients who have children between the opioid overdose and alcohol intoxication populations or a difference in the custodial relationships between patients of the opioid overdose and alcohol intoxication population. A brief literature review found no research examining the proportion of opioid and alcohol users who have children or on the custodial relationship of opioid and alcohol users, except that it is a common fear of women with addiction to lose custody of their children if they seek treatment [106]. The same review also found no previous studies that specifically looked at the difference between family-based social assistance programs and workforce and/or disability-based social assistance programs. While some people may assume that if one social assistance program was associated with increases in drug and alcohol related call volumes then other similar assistance program should

[3]Ambulance bills for OW and ODSP recipients are paid by Social Services. [105].

also be associated, but these findings dispute that. There is likely an important correlation here that bears further investigation, but that analysis would require a larger sample size and broadened dataset, including data from social services on the family composition of the patients.

5.4 Conclusion

In this chapter, I have demonstrated the importance of both fixed- and floating-point temporal influences in the distributions of paramedic call volumes. While the subset of cases examined here represent a relatively small proportion of paramedic calls and only influences on a monthly time frame were examined, these fixed and floating-point temporal influences can be found throughout the pre-hospital world and very little research has been conducted on this topic.

It is also important to note that many of these point temporal influences are likely to be highly culturally and regionally specific. As such, the findings from one region may not be applicable to another region. The idea that these point temporal influences must be considered and determined independently for each region and then included in any time series analysis of paramedic data is important and should be considered in all future analyses of any temporal scale.

Chapter 6

Conclusion

Paramedic data science is a young and evolving field, but it is also a field of research which has exceptional potential. Between the vast quantity of untapped data that exists and the unique types of information available, paramedic data has the potential to drive new and interesting areas of research.

In this thesis, we have examined the mess that is the current state of paramedic data. The lack of standardized data dictionaries makes inter-service and interprovincial comparisons complicated, while the gray nature of paramedic work makes a thorough understanding of how the PCR system is used critical to its interpretation. Next, we examined the steps necessary to clean Ontario paramedic data for use (Chapter 2). This included deciphering the structure of the dataset and updating the data from various historical periods to be compatible with the current data. We also examined the types of data that need to be adjusted from its stock form before it could be analyzed, which included a process for reviewing narrative texts for key pieces of information and converting them to a tidyverse compliant dataset.

Once our data set was ready, we examined the complexities of data point selection in the paramedic dataset (Chapter 3). While the most obvious data point sometimes seems like a good fit, it is important to consider how that data point changes over time and examine its usage as policies change. In this case, while paramedic naloxone may have been a good metric in the early stages of the opioid crisis, it has become dangerously ineffective over time, thanks largely in part due to the use of take-home naloxone kits by bystanders. We also discussed the importance of ensuring our metrics of choice are inclusive of all populations, but especially those who are most vulnerable.

Once a population of interest was determined, we examined the temporal distributions of opioids, non-opioids, and alcohol intoxication calls (Chapter 4). We found that while there were unique distributions for each population, in many cases the distribution shared similar characteristics. All three populations experienced low call volumes in the early to mid-morning followed by a peak from the mid-afternoon to late night that was unique to each population. While these distributions can help our partners in public health better plan their harm reduction activities, the idea that paramedic calls have temporal distributions which can be easily modelled and monitored opens new areas for research in both paramedic operations and health policy monitoring.

In Chapter 5, we expanded our exploration into paramedic temporal distribution to look at both fixed- and floating-point temporal influences. In this, we found that opioid and alcohol-related call volumes and temporal distributions are sensitive to the payment date of some social assistance programs, but non-opioid overdoses were not. We also found that the full moon had no effect on call volumes. While these two-point influences are relevant to the exploration of opioid overdoses, there are many other point temporal influences which can be explored for both the general call population as well as influences that are unique to sub-populations.

6.1 Domain-Specific Knowledge

Each of these areas produced unique insights into the question of the opioid crisis and the complexity of paramedic data science. One specific area I would like to take a minute to discuss is the idea of domain-specific knowledge. While I acknowledge that a non-paramedic is capable of doing paramedic data science, I do believe that without a certain level of domain-specific knowledge into the *current* operational realities of the paramedic world, the quality of insight gleaned from the data will suffer. Two specific examples come to mind from this thesis:

- The inclusion of different units in a single datum for patient age causing a central bias,
- The idea that the problem code "Non-Opioid Overdoses," which was used to select the non-opioid overdose population, likely contains a wider variety of patients than the name suggests.

In each of these cases, if a purely data-driven approach was taken, the findings would likely have been highly biased.

I also use the word *current* when referring to domain-specific knowledge with purpose. Paramedicine is evolving rapidly, and the operational realities for paramedics are evolving just as quickly. This has never been more prevalent than during COVID-19 which saw policies changing daily [12]. While I'm not sure how many paramedics are keen to follow my path and train in data science[1], the inclusion of front-line operational knowledge is key to successful study design and interpretation of findings.

6.2 Future Work

One of the purposes of this thesis was to serve as a starting block for future paramedic data science explorations. In developing the data abstraction and cleaning process for this thesis, specific efforts were made to make the R code easily adaptable and reproducible so different services could be added to the dataset and a variety of analyses run with minimal effort. As well, in the discussion sections of Chapters 3, 4, and 5 possible future expansions for each area and possible next steps were presented.

One particularly interesting area for future work would be to continue the exploration of opioid overdose into the era of COVID-19 and see what effect COVID has had on the opioid crisis. While the opioid crisis was one of the most pressing public health concerns prior to COVID-19, it has largely been overshadowed, with many of the resources previously assigned to harm reduction being re-allocated to pandemic operations. As a paramedic working on the road during the COVID-19 pandemic, anecdotal experiences indicate we would see significant changes in the opioid call

[1] Actually, I'm pretty sure it's almost none based on the number of "ewww math" comments I have gotten over the past 2.5 years.

volumes during the COVID-19 era. This is supported by pre-covid research which found that periods of high stress and isolation/lack of social supports can lead to an increased desire to use illicit drugs [107].

Another interesting area for future work will be to expand on the idea of the floating temporal influence and look at correlations between atmospheric air pollution data and respiratory and cardiac-related calls. While previous research has shown a varying relationship between air pollution and pre-hospital death data and paramedic call volumes [108]–[110], few previous studies have had access to the level of geospatial accuracy that this data set provides. By combining the clinical aspects and geospatial accuracy of paramedic data with highly accurate local air pollution data, it should be possible to model the influence of air pollution on paramedic call volumes. This would then allow us to develop better operational models for predicting paramedic call volumes as well as further show the health and social impacts of air pollution on society.

These are but a few of the potential areas for future research that could be possible with an expansion of data science techniques in paramedic data. Paramedics interact with all levels of society, most areas of health care and even many areas of social and civil services. Through partnerships between regulatory bodies, academic researchers and paramedic services, the potential uses for paramedic data are endless.

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Appendix A

Table A.1. A full listing of all possible Pick-up Location Types as of 2018.

Letter code	Pick-up Location Type
A	Airport/Heliport
B	Apartment/Condo. Building
C	Construction Site
D	Medical Office/Clinic
E	Nursing Outpost
F	Factory/Industrial Site/Railway/Dockyard
G	Hotel
H	Hospital (Acute & Non-Acute)
I	Indoor Shopping Mall
J	Jail/Prison
K	Single Store/Strip Mall
L	School/College/University
M	Mining Site/Quarry
N	Long-Term Care Home
O	Office Building
P	Sports Facility/Arena
Q	Farm
R	House/Town House
S	Street/Highway/Road
T	Fairground/Park
U	Retirement Home
V	Golf Course
W	Water/Boat
X	Restaurant/Bar
Y	Casino
Z	Other (Describe in Remarks)