Understanding Paramedic Services Demand and Response*

An Analysis of the Impact of Time-Based Factors on Paramedic Servie Demand in Toronto from 2017 to 2022

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This paper examines the trends paramedic service demand and response against time-based factors. Using the Paramedic Services Incident Data from 2017 to 2022,the analysis aims to determine the influence of temporal factors and incident types on paramedic service demand and response. The findings shows a constant paramedic response depite fluctuating service demands throughout seasons and time of the day suggesting a flaw in resource allocation. The results of this study are significant, as they can be indicators to policymakers and paramedic services during resource manadement and dispatch.

1 Introduction

"In an emergency, seconds count." (City of Toronto 2024). Emergency medical services (EMS) are essential to public health by providing care during life-threatening situations. However, Toronto's paramedic services are struggling to meet demand. Toronto Auditor General's Office reports that there were over 1,200 episodes in 2023 where no ambulances were available (Toronto Auditor General's Office 2024). To echo this report, this paper examines EMS demand using Toronto Paramedic Services' incident data from Open Data Toronto.

In this analysis, I am interested in EMS demand against time-based factors in Toronto from 2017 to 2022. I explore trends in paramedic services, such as dispatch time, incident type, and number of units dispatched per incident to identify periods of high-volume demand and low availability of resources. I find that the number of incidents requiring paramedic services is higher in summer seasons, peaking in July and in August. The lowest number of incidents are in February. I also find that the number of incident requests are lowest between 1AM and

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7AM, while the periods of high demand are between 11AM to 7PM. However, the number of paramedic units dispatched remained constant, despite the fluctuations in demand.

The remainder of this paper is organized as follows. Section 2 discusses the data source and an overview of the studied variables. Section 3 constructs a model that predicts a shortage in paramedic resources based on time factors. Section 4 presents the results and findings of the exploration of the data. Section 5 discusses implications, limitations, and suggestions for future research. Appendix A provides a detailed exploration of observational data collection methods.

2 Data

2.1 Overview

The dataset used for this analysis is titled "Paramedic Services Incident Data" and is published by Toronto Paramedic Services (Toronto Paramedic Services 2023). For this paper, the dataset is retrieved from the City of Toronto Open Data Portal.

The statistical programming language R (R Core Team 2023) is used to process, manage and visualize the data. Specifically, statistical libraries such as `opendatatoronto` (Gelfand 2022), `openxlsx` (Schauberger and Walker 2024) and `janitor` (Firke 2023) are used to simulate, download and clean the raw data. Libraries like `arrow` (Richardson et al. 2024) and `readxl` (Wickham and Bryan 2023) were used to save and read datasets. Other libraries like `knitr` (Xie 2021), `here` (Müller 2020) are used to load and to render tables. Libraries such as `gridExtra` (Auguie 2017) and `patchwork` (Pedersen 2024) are used in te visualization of the data.The library `rstanarm` (Goodrich et al. 2022) is used in the modeling process and tidyverse' (Wickham et al. 2019) is useful throughout the entire data manipulation process.

The initial dataset features data on paramedic dispatch time, type of incident, priority level of each incident, number of paramedic units arrived at scene and forward sortation area of the incident. These features are annually refreshed on Open Data Toronto by Toronto Paramedic Services.

The data used for this paper was retrieved on November 25, 2024 and was last refreshed on October 5, 2023.

2.2 Measurements

The incident data is saved in different files according to the year of incident. The variables and measurement method of the variables are preserved throughout the recorded years.

Table 1: First Ten Rows of the Paramedic Services Incident Data from 2017

Dispatch Time	Incident Type	Priority Number	Units Arrived	Location
2017-01-01 00:01:13	Medical	1	1	M4L
2017-01-01 00:03:27	Medical	1	1	M3M
2017-01-01 00:01:41	Medical	5	1	M5B
2017-01-01 00:05:53	Medical	4	1	M5V
2017-01-01 00:03:55	Medical	3	1	M1P
2017-01-01 00:08:05	Medical	4	1	M5G
2017-01-01 00:11:10	Emergency Transfer	1	1	M2J
2017-01-01 00:06:20	Medical	4	1	M1B
2017-01-01 00:05:31	Medical	3	1	M2R
2017-01-01 00:07:16	Medical	5	1	M5S

Table 1 is a sample of the 10 first entries in the incident data in 2017. Each row in the dataset represents a unique incident. "Dispatch Time" is the precise time when the first paramedic unit was assigned to an incident. This is measured in year, month, date, hour, minutes, and seconds. "Incident Type" is the category assigned to the incident by the dispatcher based on the information provided by the 9.1.1. caller(s). The possible categories of incident are medical emergencies, emergency transfers, fire-related incidents and motor vehicle accidents. "Priority number" represents the urgency of an incident with 1 being the most urgent and 5 being the least. The priority number is measured by the Medical Priority Dispatch System (MPDS) based on the information provided by the 9.1.1. caller(s). "Units Arrived" is the total number of paramedics that arrived on the scene of incident. This is measured by counting the number of different paramedic units who were dispatched and responded to the incident. Units part of this count do not have to be simultaneously present, and a unit who leaves the scene and comes back afterwards is considered 1 count. "Location" is the general location of the incident based on Postal Code Forward Sortation Areas. This is determined as the first three characters of the postal code of the incident location.

2.3 Variables of Interest

In the analysis dataset, most variables were constructed using the variables in the raw dataset. From the original dataset, "Dispatch Time" was broken down into four separate variables in the analysis dataset: "Year", "Month", "Day of the Week" and "Hour of the Day". The aim for this construction is to isolate the effect of each temporal factor on the paramedic incident request paramedic response. While holding the time variables and the "Incident Type" variable constant, two more variables were constructed from the "Units Arrived" variable from the raw dataset: "Average Units Arrived" and "Number of Incidents".

Table 2: Ten First Rows of the Analysis Data on Paramedic Services Incident Data from 2017 to 2022

Year	Month	Day of the Week	Hour of the Day	Incident Type	Average Units Arrived	Number of Incidents
2017	Jan	Sun	0	emergency transfer	1.3	6
2017	Jan	Sun	0	fire	2.7	3
2017	Jan	Sun	0	medical	1.1	179
2017	Jan	Sun	0	motor vehicle accident	1.7	6
2017	Jan	Sun	1	emergency transfer	1.0	2
2017	Jan	Sun	1	fire	4.0	1
2017	Jan	Sun	1	medical	1.0	182
2017	Jan	Sun	1	motor vehicle accident	1.7	3
2017	Jan	Sun	2	emergency transfer	1.0	4
2017	Jan	Sun	2	medical	1.0	143

Table 2 is a sample of the analysis dataset used in this paper. The variables of interest of the analysis dataset are:

- Number of incidents:This variable represents the total count of emergency incidents recorded for each unique combination of time and incident-type factors. This is the outcome variable in the model, since it reflects the demandfor paramedic services.

- Average number of units arrived: This variable reflects the average number of paramedic units dispatched and arrived at the scene for a given combination of incident type, time, and date. This is another outcome variable , since it provides insight into resource allocation.

- Incident Type: This categorical variable describes the nature of each emergency, such as medical emergencies, fire-related incidents, motor vehicle accidents, or emergency transfers. It captures the diversity of incidents and is useful for exploring differences in ressource needs

- Year: The year the incident occurred, capturing long-term trends in incident frequency.

- Month: The month of occurrence, which higlights seasonal trends

- Day of Week: The day on which the incident took place, accounting for patterns related to weekdays versus weekends.

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- Hour: The hour of the day, capturing diurnal patterns in emergency service demand.

3 Model

3.1 Model set-up

We run the model in R (R Core Team 2023) using the `rstanarm` package (Goodrich et al. 2022). Default priors from `rstanarm` are applied. The estimating equating is as follows:

Define y_i as the number of incidents observed for a specific combination of factors. Then, μ_i is the expected number of incidents based on temporal and incident-specific predictors.

$$y_i | \mu_i, \sigma \sim \text{Normal}(\mu_i, \sigma) \tag{1}$$

$$\mu_i = \alpha + \beta_{\text{year}} \cdot \text{year}_i + \sum_{k=1}^{11} \beta_{\text{month},k} \cdot \text{month}_{ik} + \sum_{j=1}^{6} \beta_{\text{day},j} \cdot \text{day}_{ij} \tag{2}$$

$$+ \beta_{\text{hour}} \cdot \text{hour}_i + \sum_{t=1}^{3} \beta_{\text{incident},t} \cdot \text{incident}_{it} + \beta_{\text{units}} \cdot \text{avg\_units}_i \tag{3}$$

$$\alpha \sim \text{Normal}(0, 2.5) \tag{4}$$

$$\beta \sim \text{Normal}(0, 2.5) \tag{5}$$

$$\sigma \sim \text{Exponential}(1) \tag{6}$$

In this model, we define the variables as follows:

- y_i is the number of incidents observed for a specific combination of factors
- μ_i is the expected number of incidents based on predictors
- α is the intercept term, representing the baseline number of incidents.
- β_{year} is the coefficient for the year variable.
- β_{month} is the set of coefficients for the month of the year.
- β_{day} is the set of coefficients for the day of the week.
- β_{hour} is the coefficient for the hour of the day.
- β_{incident} is the set of coefficients for the incident types.
- β_{units} is the coefficient for the average number of units arriving on scene
- σ is the standard deviation of the residuals, representing unexplained variability in incident counts.

3.1.1 Model justification

For this analysis, a Bayesian Generalized Linear Model (GLM) was chosen to predict incident call counts as a function of temporal factors, incident type, and resource allocation. This approach provides the flexibility to model log-transformed continuous outcomes and includes prior beliefs about the relationships between predictors and the outcome. The Bayesian framework quantifies uncertainty in parameter estimates and predictions, which is useful in our context where variability and uncertainty are prevalent. This model is appropriate given the observed overdispersion in the count data.

In Bayesian modeling, priors were defined to reflect plausible values. A Normal$(0, 10)$ prior was used for the intercept (α) to allow a wide range of baseline incident counts across predictor combinations. Predictor coefficients (β) were assigned a Normal$(0, 2.5)$ prior to accommodate moderate effect sizes without being too restrictive. The residual standard deviation (σ) was given an Exponential(1) prior to emphasize smaller residual errors. These priors avoid constraints that are too narrow, reducing bias in the estimates

This model relies on several assumptions. First, it assumes a linear relationship between predictors and the log-transformed outcome variable, which simplifies interpretation. The model also assumes residuals follow a Gaussian distribution, consistent with the log-transformation of the outcome variable. Despite its strengths, the model has limitations. It does not explicitly model nonlinear relationships or interactions,like those between temporal and incident type variables, which could capture more complex dynamics. Finally, the Gaussian residual assumption may be inappropriate in certain cases of extreme overdispersion.

Several alternative models were considered. Poisson regression, a natural choice for count data, was notr chosen due to overdispersion in the outcome variable. Negative binomial regression was also considered, but does not incorporate prior beliefs or uncertainties as naturally as Bayesian methods.

Ultimately, the Bayesian Gaussian GLM was selected since it can handle continuous log-transformed data and include prior beliefs while still being digesteable.Through Bayesian inference, the model quantifies uncertainty and provides a probabilistic framework ideal for emergency response planning. This approach ensures actionable predictions for resource allocation decisions.

4 Results

The results of the model can be found in Table 3.

Table 3: Model Summary of Incident Count

	mean	mcse	sd	10%	50%	90%	n_eff	Rhat
(Intercept)	0.2	1.41	137.69	-174.21	1.83	174.28	9511	1
year	-0.01	0	0.07	-0.09	-0.01	0.08	9514	1
month.L	2.3	0	0.39	1.8	2.3	2.81	6858	1
month.Q	-1.3	0	0.39	-1.81	-1.31	-0.81	9371	1
month.C	-2	0	0.4	-2.5	-2	-1.48	9799	1
month^4	3.5	0	0.39	2.99	3.49	4	7759	1
month^5	-0.07	0	0.39	-0.58	-0.07	0.42	8417	1
month^6	1.29	0	0.39	0.79	1.29	1.79	8579	1
month^7	-1.56	0	0.4	-2.07	-1.55	-1.04	7662	1
month^8	1.81	0	0.38	1.33	1.81	2.3	8106	1
month^9	-0.06	0	0.39	-0.56	-0.06	0.45	8301	1
month^10	0.91	0	0.4	0.4	0.9	1.41	8836	1
month^11	-0.44	0	0.4	-0.94	-0.45	0.08	8626	1
day_of_week.L	0.88	0	0.3	0.5	0.88	1.25	9399	1
day_of_week.Q	-0.71	0	0.3	-1.09	-0.72	-0.33	8389	1
day_of_week.C	-0.38	0	0.3	-0.76	-0.38	-0.01	8797	1
day_of_week^4	-0.84	0	0.31	-1.23	-0.84	-0.44	9495	1
day_of_week^5	-0.08	0	0.3	-0.46	-0.08	0.32	10495	1
day_of_week^6	-0.22	0	0.3	-0.61	-0.22	0.17	7663	1
hour	1.2	0	0.02	1.18	1.2	1.22	7106	1
incident_typefire	-6.63	0.01	0.5	-7.27	-6.62	-5.99	5198	1
incident_typemedical	126.41	0	0.3	126.04	126.41	126.8	5121	1
incident_typemotor vehicle accident	0.16	0	0.3	-0.22	0.16	0.55	6548	1
avg_units_arrived	1.33	0	0.2	1.08	1.32	1.58	6328	1
sigma	22.52	0	0.08	22.41	22.51	22.62	6986	1
mean_PPD	44.41	0	0.16	44.2	44.41	44.62	6063	1
log-posterior	-175993	0.09	3.54	-175998	-175993	-175989	1692	1

The Bayesian GLM model, based on 38,494 observations and 24 predictors, has a posterior predictive mean (mean_PPD) of 44.4, which aligns with observed incident counts. This shows that the model captures variability.

Temporal factors play a role in determining incident volume. The coefficient for hour (mean = 1.2) shows predictable variations in demand throughout the day, with highly precise estimates (sd = 0.0). Monthly and daily trends are captured through polynomial terms, reflecting the nonlinear nature of incident occurrences across different times of the year and week.

The analysis suggests the dominance of medical incidents in driving overall incident counts. The coefficient for medical calls (mean = 126.4) is much higher than the coefficient for fire-related incidents (mean = -6.6) and the coefficient for motor vehicle accidents (mean = 0.2). This shows that medical emergencies is the primary source of paramedic service demand, requiring special attention in operational planning.

The positive relationship between the average number of units arriving and incident counts (mean = 1.3) suggests that resource allocation is another determining factor. There is a correlation where increased resource availability may correspond to higher incident volumes. This reflects areas of concentrated demand and hints at resource allocation strategies.

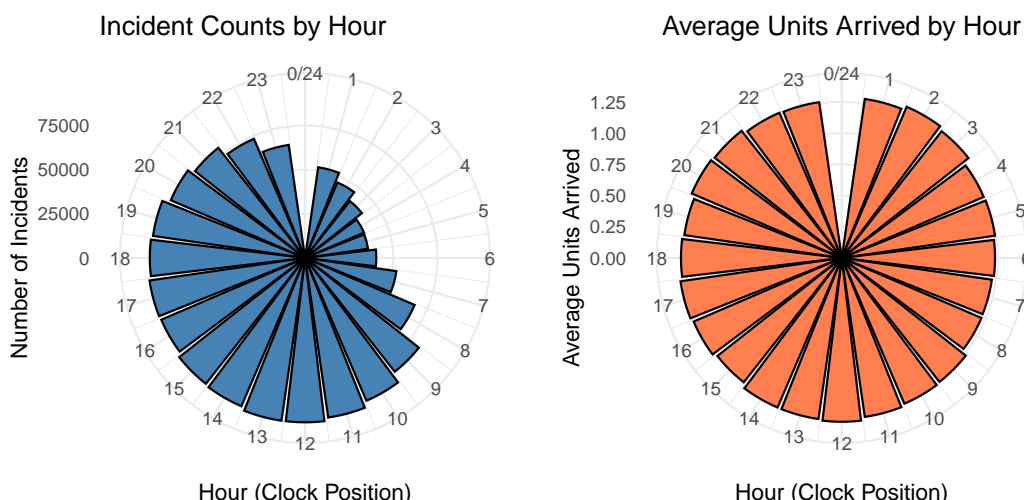## 4.1 Hour of the Day on Paramedic Incident Demand and Reponse

Figure 1: Paramedic Incident Counts and Number of Units Arrived on Scene by Hour of the Day from 2017 to 2022

Figure 1 shows distinct patterns in incident demand and resource allocation throughout the day. The number of incident calls is lowest during the early morning hours, from 1 AM to 7 AM. This suggests that fewer emergencies or incidents occur during these hours, possibly due to lower activity levels at night. Conversely, from 11 AM to 7 PM, there is a noticeable peak in the number of incident calls, reflecting an increased demand during daytime hours.

The number of units arriving at the scene remains constant throughout the day, as shown in Figure 1. This suggests that the response resources, measured by the average number of units dispatched to incidents, do not vary by time of day. While demand fluctuates based on

the time of day, the resource allocation appears to be stable, regardless of whether it's early morning or peak daytime hours.

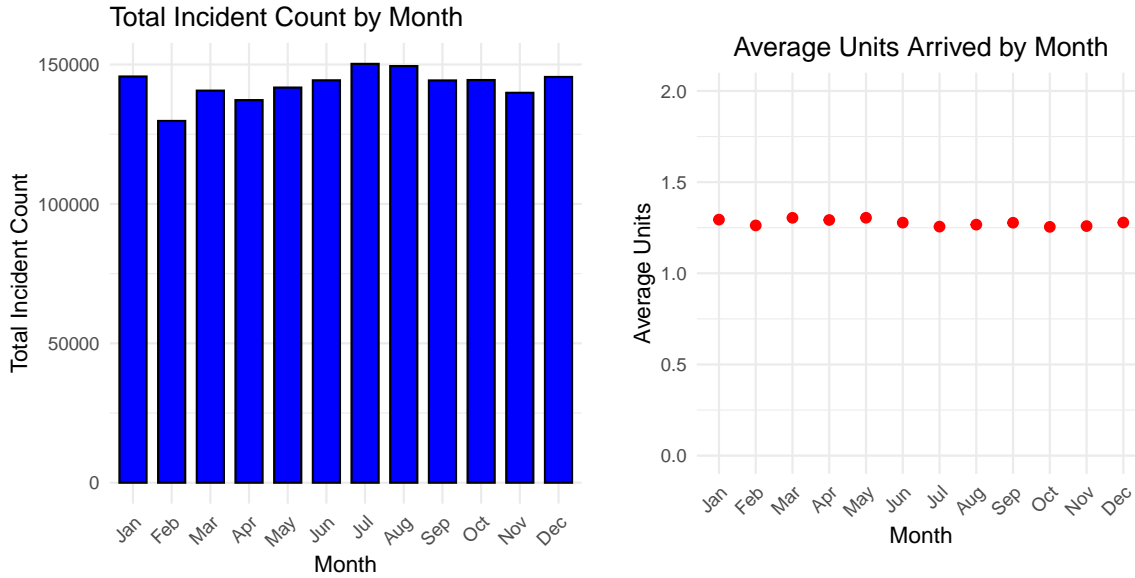## 4.2 Month of the Year on Paramedic Incident Demand and Reponse

Figure 2: Paramedic Incident Counts and Number of Units Arrived on Scene by Month of the Year from 2017 to 2022.

Figure 2 shows the incident count and unit deployment over the months. From February to July, the number of incidents gradually increases, with a peak occurring in July and maintained in August. This suggests that during these months, the demand for emergency services rises significantly. After the peak, the number of incidents declines, though the decrease is slow and continuous, indicating a steady reduction in demand as the year progresses. A drop in paramedic service demand drops in February, which represents the lowest point of the year for incidents. Despite these fluctuations in the number of incidents, the average number of units dispatched to each incident remains constant throughout the entire period. There is a consistency in the number of units deployed, regardless of the demand variations.

5 Discussion

5.1 Temporal Trends in Incident Demand

The analysis of incident counts in Figure 1 and Figure 2 reveals clear temporal patterns, with a marked increase in demand from February to July, peaking in the summer months of July and August. This trend in demand for emergency services suggests that higher temperatures or other environmental factors may be influencing the frequency of incidents.

After the peak, the decline in incidents is gradual, with a sharp drop occurring in February, marking the lowest demand for services. This decline may reflect seasonal changes or a reduction in certain types of incidents during colder months. The consistency in demand across the year, though fluctuating, provides valuable insights into the factors driving incident frequency and how emergency services might adjust their strategies to accommodate these trends.

5.1.1 Global Warming in Increasing Incident Demand

The average global temperature on Earth has increased by at least 1.1° Celsius (1.9° Fahrenheit) since 1880. This is a large increase considering the majority of the warming has occurred since 1975, at a rate of roughly 0.15 to 0.20°C per decade (Lenssen et al., n.d.). This means that there are more increasingly hot days in the summer, and heat-related emergencies are more common. (The Climate Institute 2024). This can explain an increase in medical emergencies due to heat waves, and fire-related emergencies especially in drier and hotter areas of Toronto.

5.2 Consistency of Resource Allocation

Despite variations in incident demand, the number of units dispatched to each call remains constant over time. This consistent deployment strategy suggests a rigid approach to resource allocation, where the same number of units are sent to all incidents regardless of demand fluctuations. This is an indicator of inefficient resource management or of lack of paramedic resources. This aligns with Toronto Paramedic Services' Executive Summary in 2024. The Auditor General highlights that from 2019 to 2023, the average paramedic response time increased by 31% and by 29% for incident calls of priority 2 and 3 (Anderson 2024). A more dynamic resource allocation model that adjusts the number of units based on the volume of incidents could optimize service delivery and response times.

5.3 Implications for Policy and Operational Strategy

The findings from this analysis shows the importance on temporal factors in demand forecasting to optimize unit deployment based on incident volumes. Policymakers and emergency services can reevaluate current resource allocation practices such that units are deployed where and when they are most needed.

5.4 Weaknesses and Next Steps

One limitation of this analysis is the assumption that the number of units deployed should be constant across all incidents. This approach do not account for complexities of different types of incidents, which could require adjustments in resource allocation. Further research could explore how incident complexity (e.g., severity, location, time of day) impacts the need for additional or fewer units, which can also contribute to resource planning.

Additionally, while the temporal patterns in demand are evident, this study does not explore external factors that might influence incident frequency, such as public holidays, or special events. Future work could incorporate these variables to refine demand forecasting models. A deeper understanding of these external factors could help emergency services anticipate and prepare for periods of high demand, ensuring that resources are allocated more effectively.

Lastly, the analysis could be expanded by including geographical data to examine how resource allocation strategies might differ across regions. This approach could provide insights into local needs and help tailor emergency response plans to the specific needs of different communities.

Appendix

A Collection and Analysis of Observational Data

This appendix provides a deep dive into how observational data is collected, how to ensure its credibility, and how new data can be collected responsibly. The strategies for minimizing bias, controlling for confounding variables, and maintaining high data quality are key for making credible, robust conclusions in observational research.

A.1 Observational Data

A.1.1 What is Observational Data?

Observational data is the information collected through direct observation of events, behaviors, or conditions without any interference or manipulation by the researcher. Unlike experimental data, where participants are randomly assigned to different treatments, observational data comes from naturally occurring phenomena. In the case of this study, the data is derived from emergency response logs, which capture real-world incidents without any direct control over the conditions under which the data is collected.

The key challenge with observational data is the risk of selection bias or confounding factors. For example, certain types of incidents (e.g., medical emergencies) might be more likely to be recorded during peak hours, potentially skewing results if this factor is not considered. Additionally, time of day, geographical factors, or incident severity could all influence data patterns, which requires careful accounting for these elements to ensure accurate conclusions.

A.1.2 Why Focus on Observational Data?

The advantage of working with observational data is that it allows for the analysis of real-world scenarios without needing to rely on artificial conditions. In the case of emergency response data, observational data points at how resource allocation occurs in response to varying incident types and times of day. Collecting new observational data allows researchers to analyze existing systems, such as healthcare, traffic management, and emergency services, which are inherently complex and often not amenable to traditional experimental study designs.

Moreover, since observational data is often more readily available compared to experimental data, it can offer quicker and cheaper insights. This is especially valuable in areas like emergency management, where real-time data is essential for decision-making and resource deployment.

A.2 Credibility in Observational Data Collection

A.2.1 Key Challenges in Observational Data Collection

Observational data is subject to several challenges that can affect its credibility. These challenges include bias, measurement errors, and confounding variables.

- Bias: This arises when certain groups or types of data are over- or underrepresented due to the way the data is collected. For example, if incidents occurring in certain neighborhoods or regions are more likely to be logged than those in others, the data could be biased, leading to inaccurate conclusions.

- Measurement Errors: Data collection in observational studies often depends on human input (e.g., data entry by emergency responders), which may lead to errors. These errors could involve incorrectly logging incident types, missing data points, or misreporting times.

- Confounding: In observational studies, certain unmeasured variables might affect both the predictor and the outcome variable, leading to misleading associations. For example, weather conditions or road closures could influence the frequency of certain incidents, but if these factors are not accounted for, the results may not accurately reflect the true relationships.

A.2.2 Strategies for Ensuring Credibility

To ensure that the observational data collection process remains credible, several strategies can be implemented:

- Data Validation: Continuous validation checks to ensure that the data is accurate and complete. This involves cross-checking reported incidents with independent sources (e.g., by reviewing video footage or corroborating with nearby emergency service providers) to ensure consistency.

- Standardization of Data Entry: Establishing standardized protocols for data collection can reduce errors introduced by subjective decisions. For instance, ensuring that emergency responders log incidents using consistent terminologies or formats minimizes the potential for misinterpretation.

- Minimizing Bias: To reduce bias in observational data, the data collection process should be designed to capture a representative sample of all incidents. For example, stratified sampling based on time of day, incident type, and location can help ensure that different subgroups are equally represented in the dataset. Weighting the data to account for underrepresented incident types (e.g., incidents that happen more frequently at night) can also help mitigate bias.

A.3 Collecting New Observational Data

If collecting new observational data were part of this study, careful planning and execution would be necessary to ensure data credibility. Here are the steps I would follow:

A.3.1 Establish Clear Objectives

Defining clear research questions can help to outline the data collection methods. For instance, "How do incident types affect the allocation of emergency units during peak hours?" Understanding what variables need to be captured will guide the data collection process and ensure that only relevant information is recorded. This includes variables such as incident type, number of units dispatched, time of day, and response times.

A.3.2 Define Sampling Procedures

Given that observational data often suffers from biases related to time or location, it would be important to define a sampling procedure that captures a representative range of incidents. This could include:

- Stratified Sampling: Ensure that incidents are captured across different times of day (morning, afternoon, night) and different days of the week.

- Random Sampling: Although observational data is often non-random, incorporating a random sampling element (e.g., randomly selecting some incidents for additional review or analysis) could help ensure a broader representation.

A.3.3 Data Logging Protocol

A standardized data entry protocol ensures consistency across all data entries. For instance, data entry personnel (e.g., emergency responders or dispatchers) should be trained to use the same terminology for incident types and categories. This can help prevent variations in the way incidents are logged.

Also, using automated systems to capture data (e.g., GPS systems to log the exact time and location of incidents) can reduce human error and provide more reliable information. Any manual entries, such as the number of units dispatched, should be carefully checked against existing records to ensure accuracy.

A.3.4 Ethical Considerations and Data Privacy

In collecting new observational data, particularly from emergency responders, it is important to adhere to strict ethical guidelines. This includes ensuring the confidentiality and privacy of individuals involved in incidents. All personally identifiable information should be anonymized or removed from the dataset, ensuring compliance with ethical standards and data protection regulations.

A.3.5 Use of Simulation for Data Collection

To simulate real-world data and anticipate potential biases or gaps, simulation studies can be valuable. For example, by simulating different incident scenarios (e.g., a high volume of medical emergencies or vehicle accidents during rush hour), we could test how well the data collection process captures these extremes. This would help identify areas of improvement in the observational process and validate the model's robustness when applied to actual data.

A.4 Weaknesses and Limitations

Despite these strategies, there are limitations in the use of observational data:

- Unobserved Confounding: Some factors, such as hidden traffic patterns or covert road closures, might influence the data in ways that are difficult to account for.

- Temporal and Spatial Biases: Certain periods (e.g., holiday seasons or extreme weather events) might not be equally represented in the data, affecting the results.

- Measurement Errors: Even with standardization, some degree of measurement error is inevitable. These limitations emphasize the importance of combining observational data with other methods, such as simulation studies or complementary data sources, to validate findings and improve the credibility of the conclusions drawn.

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