Catching Red Flags: Forecasting Emergency Department Visits Linked to Extreme Heat Events (EHEs)

CSCI 6410 RESEARCH PROPOSAL

ALEXANDRA DEL FAVERO-CAMPBELL, ERIC POARCH, HARSH KAUSHIK, TSZ KIN SIU

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Abstract

Extreme heat events (EHEs) are among the most lethal and financially burdensome environmental hazards in the world. The unprecedented surge in medical emergencies during EHEs poses dire consequences and challenges for emergency department (ED) staffing and financial planning considerations. Improving predictive modelling of emergency department visits to meet increased need during these surges is crucial to health services research and planning. Our research project aims to enhance predictive models for ED visits to address these ever-growing spikes in demand. We propose an ecological prediction model using time series data to forecast ED visits linked to EHEs. Using environmental monitoring and administrative health data collected between April 1st, 2016 and March 31st, 2023, we assess the impact and association between local weather, air quality, socio-demographic variables and ED visit volumes. We identify key morbidity indicators and illness severity metrics to develop a neural network model for predicting future ED utilization. By providing a novel modeling approach in a Canadian context, this study has the significant potential to provide actionable insights for healthcare service planning and resource allocation during extreme heat events.

Lay Summary

Extreme heat events (EHEs), such as heatwaves, often lead to significantly increased usage of emergency departments' (EDs) resources due to health problems related to unusually high temperatures. By analyzing historical patient data, such as age and the locations of the EDs they visited, we can identify those most at risk during future extreme heat events. With six years of health data, we can also predict the types and severity of illnesses that may need treatment. Our model will be the first in Canada to use weather forecasts to predict when and where additional ED staff and hospital resources will be needed, the types of staff required, and the associated costs, during EHEs. This will help hospitals better prepare for future EHEs, ensuring they have the necessary resources to manage unprecedented rises in patient loads effectively during extreme climatic conditions.

1. Introduction

In the past year, the world has experienced 11 consecutive months of record-breaking temperatures, including 76 extreme heat events (EHEs) across over 90 countries[1]. In fact, 2023 was recorded as the hottest year on record[2,3], with around 78% of the global population living through at least 31 days of extreme heat[1]. Moreover, it is anticipated that these extreme heat events will only intensify in frequency, duration, and severity in the future[4,5], with strong evidence that these climatic disasters will pose serious threat to all aspects of life, including threats to public health and the economy[6].

Extreme heat events are currently one of the most dangerous and costliest environmental threats in the world[6–8], frequently reported as killing more people than all other natural disasters combined[9–11]. The economic burdens include increased healthcare costs[7], reduced labor productivity[12], and damage to infrastructure, further destabilizing economies. Emergency healthcare systems, in particular, face unprecedented strain and costs, as extreme heat exacerbates existing health conditions and increases incidence of heat-related illnesses. For example, the 2-week long EHE that occurred in California in 2006 was estimated to cost hospitals $14.1 million in emergency department (ED) visits alone[8], with other experts stating that regardless of future warming scenarios, treatment costs and ED visit rates are destined to significantly increase[13].

Canada has not been immune to these challenges, with British Columbia facing one of the deadliest and costliest disasters in provincial history in 2021[14]. This 6-day event resulted in approximately $12 million in healthcare costs attributed to the EHE[15] and caused a significant surge in ED visits. According to Clark and colleagues[16], hospitals within the Greater Vancouver area were significantly overwhelmed with an additional 282 ED visits per day compared to baseline levels and reported delayed effects continuing a week later with 181 more ED visits per day. Needless to say, this surge placed immense additional pressures on healthcare facilities and hospital resources, highlighting their unpreparedness for such extreme conditions and attributing to hundreds of preventable deaths[17].

The ED is one of the most critical areas in any hospital[18] and the Canadian health system is already working with limited resources. Thus, being able to accurately predict EHEs and forecast future healthcare demands would be an invaluable support for hospitals to prevent high demand and significantly mitigate these preventable impacts by enabling better resource allocation, reduce overall costs, and improve health outcomes. Several predictive models have been developed in the last decade to attempt to predict high demands within a hospital setting, aiming to better manage staff rosters and hospital beds[18,19]. However, very few have attempted to forecast ED visits within the lens of EHEs and there is an overall lack of applicable context to a Canadian health system and climate. A proactive forecasting tool could ultimately enhance the resilience of Canadian health systems and help make effective informed decisions to better withstand extreme health events.

2. Literature Review

A review of relevant literature yielded 43 publications, in which 22 publications analyzed associations between extreme heat and health and 21 peer-reviewed articles evaluated ED visit forecasting models (Appendix S2).

2.1. Previous Work on Extreme Heat Events and Health

Exposure to an EHE can both exacerbate existing chronic disease and cause acute illness outside of directly heat related illnesses[20]. Chronic disease vulnerabilities include existing diabetes mellitus and cardiovascular, respiratory, and kidney disease, while common acute diagnoses include renal failure and ischemic heart diseases, such as myocardial infarction. Studies of the 2021 Pacific Northwest heatwave found, respectively, 49.1%, 42.4%, and 147.8% increases in diabetes mellitus, pneumonia, and acute kidney failure in Vancouver[16], and a 38% increase in acute myocardial infarctions in Seattle[21]. In order to capture the most relevant health outcomes to the study setting, 7 of the 21 studies included were specific to the 2021 Pacific Northwest heat wave and related health outcomes, while the remaining studies analyzed health outcomes using transportable populations or used longitudinal data more similar in design to our current study[1,7–9,20,22–31].

2.2. Previous Work Forecasting Emergency Department Utilization

Many individuals seek medical care during EHEs, but we have limited understanding of how to predict their impact on hospital operations. Wettstein et al. (2024)[21] conducted a study on the extreme heat event that occurred in the Pacific Northwest in 2021 and its impact on healthcare utilization. They examined how this EHE affected ED visits and hospital operations within a large health system. In this study, they used past electronic medical records from three different hospitals in Seattle to compare healthcare during EHEs. They primarily used interrupted time series analysis to see how the EHE affected ED visits. They compared how crowded the EDs were during the EHE to the period before the event using Student's t-tests and chi-squared tests. Finally, they incorporated multivariable Poisson regression to identify risk factors for hospital admissions and heat-related illnesses.

Emergency departments have also kept working on improving patient flow without lowering the standard of healthcare quality. Hunter-Zinck and colleagues[32] aimed to see if it was possible to predict clinical ordering behavior when a patient first checks into the ED. They used a triage dataset to train machine learning models (e.g., partial least squares classification, support vector machine, random forest, and MLP) to predict the medical orders doctors would make during an ED visit. They tested four different machine learning models using two distinct methods: binary relevance and random k-labelsets. They evaluated the performance of the algorithms, identified the important factors, and conducted a study to understand how these models would affect costs and the time patients would spend in the ED. They found that the overall performance was best when predicting orders independently by using a multilayer perceptron. Similarly, other experts, such as Murtas et al.[18], studied ED visits from January 2014 to December 2019 in Milan's five largest hospitals using regression models with ARIMA errors. They allowed ARIMA parameters to differ among hospitals based on their unique characteristics and measured the accuracy of their predictions using the mean absolute percentage error (MAPE). Their results showed good prediction of very high demand days with a sensitivity as high as 90% (depending on exceedance level and hospital) and an MAPE globally smaller than 8.1%.

Lastly, an approach taken by Park and Kim[33] specifically used machine learning in a heat-health context by attempting to define heatwave thresholds by examining the complex relationship between heat-related health issues and weather conditions. To establish thresholds for ED visits due to heat-related illnesses, they collected both ED visit records for heat illnesses, as well as 19 different weather variables, from 2011 to 2016. They employed Multivariate Adaptive Regression Splines (MARS) models to explore the data's non-linear patterns. This uncovered that thresholds varied based on the demographics of the affected individuals, as well as the specific locations and timing of EHEs. The study highlighted the importance of average daytime temperature as a key factor in defining heatwave thresholds. Overall, the results showed that there are opportunities to improve heatwave warning systems by considering how different people react to extreme heat events and improved the basic understanding of the effects of heatwaves on human health.

2.3. Summary of Gaps in the Empirical Literature

In summary, although much is now known about the dangers and relationship between extreme heat and health and many have developed prediction models within the context of hospital EDs, very few have attempted to incorporate the concept of EHEs into a forecasting model. As ED visits are unavoidably subject to fluctuations and many countries have seen substantial increases in ED visits in the last decade[34], the majority of studies evaluating forecasting in EDs have been published recently, with many proposed approaches to predictive modeling but no gold standard method. However, very few studies have attempted to link temporal periodicity, local weather conditions, and pollution to ED visits, let alone within the context of EHEs. Of the models that have been attempted, most only include narrowly-defined heat-related illnesses and not other outcomes commonly associated with EHEs (e.g., acute renal failure). To our knowledge, there is no study linking all of this information together to forecast ED visits within the unique Canadian climate and healthcare system, making our project unique.

3. Research Question and Objectives

3.1. Key Research Questions

Our work will expand upon previous models that analyzed single extreme heat events and those that analyzed narrowly define outcomes by asking the following questions: 1) What are key environmental and sociodemographic factors that can be used to predict ED utilization during recent extreme heat events across British Columbia? 2) What are the key impacted diseases of extreme heat event-related ED visits? 3) Can a temporally-based machine learning approach accurately forecast ED visit exceedance levels and categorize them into specific high-risk diagnosis group cases before, during, and after EHEs occur?

3.2. Rationale and Objectives

This study aims to identify key environmental and sociodemographic factors that predict ED diagnoses and visit volume during EHEs. Specifically, our objectives are to identify weather and air quality conditions (1) and sociodemographic vulnerabilities (2) associated with ED visits during recent EHEs in British Columbia. We will describe medical morbidities (3) that occurred more frequently during recent heat events in British Columbia and their severity. Lastly, in order to enhance our understanding of the impacts of extreme temperatures on health and improve emergency response strategies, this comprehensive data collection will form the basis for developing a predictive model to forecast the impacts of future EHEs on ED visit volume (4).

4. Methods

4.1. Data

4.1.1. Environmental Data

This study collects two types of environmental indicators: 1) temperature and 2) air pollution. Temperature directly determines the occurrence of EHEs. Other relevant meteorological parameters, such as humidity, atmospheric pressure, and wind, will be included to represent the atmospheric interaction affecting the relationship between temperature and health response. Air pollution, including airborne fine particulate matter (e.g., PM2.5 and PM10), is closely related to heat-related weather hazards. Fine particulate matter is particularly aggravated during wildfires, a common occurrence in the summer months in British Columbia. Moreover, ground-level ozone (O_3) concentrations tend to peak in the summer, as well[35]. Historical climate data measured at the weather monitoring stations are publicly available from the Environment and Climate Change Canada (ECCC)[36]. For pollutant concentrations, the National Air Pollution Surveillance (NAPS) program releases validated measurements[37]. As its data availability has a 1-year lag time and some stations are not reporting data every year, we will also incorporate data from AirNow, an open-source platform with a partnership with the British Columbia Ministry of Environment and Climate Change Strategy that is readily accessible. These historical time series will be used as predictors in model training. To better resemble the actual operation, when making a prediction in the future steps, we will employ forecasted data for representation. For this, the Regional (Air Quality) Deterministic Prediction System (RDPS/RAQDPS) openly offers air quality and weather forecasts every 6 hours for up to 84 hours through the Meteorological Service of Canada GeoMet data services[38].

4.1.2. Health Data

De-identified health data will be retrieved from the National Ambulatory Care Reporting System (NACRS) and Medical Services Plan (MSP) administrative health databases through Population Data BC. The NACRS contains data on ambulatory care in Canada and is reported to by most EDs in British Columbia, including around 70% of ED visits over the study period[39]. The diagnosis of each ED visit record in NACRS has assigned international classification of disease (ICD) codes for the main problem and other secondary conditions identified[40]. The MSP includes provider payment, encounter records, and the patient registration file. Encounter records include data on fee-for-service billed ED visits and diagnosis codes. The patient registration file is collected for residents of British Columbia insured under MSP and includes data on the demographic variables that will be used in our descriptive analysis.

For the data integration, we will request the health data accessible through Population Data BC for the study period 2016/17 through 2022/23. Unique patient and provider IDs are created that connect the health datasets over the study period. ED visits will be derived from this data based on the methodology established by Peterson et al.[39]. The method uses both deterministic and probabilistic approaches to link the administrative datasets into a comprehensive dataset of ED visits occurring in British Columbia and patient registry data on demographic variables.

4.2. Study Design

4.2.1. Defining Extreme Heat Events (EHEs)

To date, there is no clear and concrete definition for an EHE. However, EHEs are typically characterized by their exceedance over a given intensity *threshold* and a given sustained *duration*[30]. Based on several definitions from different publications[26,28,30], for the sake of this project, an EHE will be defined as unusually high temperatures than average for a given place and time where the daily maximum ambient temperatures are in the upper 90th percentile and these conditions last at least 3 consecutive days. Thus, exceedance of the temperature threshold for less than 3 days will not be regarded as an EHE series.

4.2.2. Study Period

We will construct ecological time series of environmental indicators, as well as ED visits and patient attributes from administrative health databases between April 1st, 2016 and March 31st, 2023. This study period captures relevant wildfire years that had a significant impact on air quality (2017, 2018, 2021)[41] and years with EHEs that resulted in significant surges in ED use (2021, 2022)[16,42]. We will include only the months of April to October in our dataset, with winter months removed due to the likely absence of heat-related events. Since administrative health data is collected by fiscal year, this aligns with restricting to quarters 1 and 2 of each fiscal year.

Since this study period includes the unprecedented COVID-19 pandemic, we will exclude ED visits explicitly stating COVID-19 related symptoms as the most likely diagnosis (i.e., ICD-10 codes: U07.1 - U07.7). These surging medical demands during an outlier period of a large-scale pandemic are hard to predict. Nevertheless, the pandemic years also provide a scenario for conducting sensitivity analyses on our fitted model. For this, we will evaluate how ED utilization related to different diseases commonly triggered in EHEs varied during the COVID-19 pandemic in the 2020-21 fiscal year. This will help us understand the potential drop in the model performance in abnormal circumstances caused by external factors.

4.2.3. Participants

We will construct a cohort for the study period drawn from all adults 19 years of age and older in British Columbia insured by MSP with an ED visit record between April 1st, 2016 and March 31st, 2023 to address the research question. Vital statistics and deaths data will be used to identify people who died during the study period to exclude them from the analyses.

4.2.4. Spatial Data Alignment

We will include all hospitals from the 5 Health Authority regions in British Columbia in this study. We will focus on the adult and elderly ED visits for our disease outcomes of interest. Thus, pediatric hospitals will be excluded. Each hospital is typically tied with a Community Health Service Area (CHSA) in the province. Data of the meteorological and ambient air pollutant monitoring stations located within the same CHSA of the hospital will be mapped to the hospital-specific ED visit attributes, aggregated by taking simple averages. To align with the forecast intervals of the environmental variables, the ED visit counts will be summed over 6-hour periods. If there is no station within the same CHSA, the upper level in the hierarchy of spatial boundaries (i.e., Local Health Area) will be considered.

4.3. Target Variables

Our primary outcome is the number of ED visits, which will be further be stratified by the Canadian Triage and Acuity Scale (CTAS) and diagnoses via ICD codes of interest (Appendix S1).

Diagnosis codes from ICD-9 and ICD-10 will be used to determine the responsible diagnosis for each ED visit over the study period. Other than the exclusion of COVID-19 symptom-related ED visits, scheduled visits for daytime surgery or clinics happening in the ED will be excluded. CTAS informs the severity (5 levels) and types of presenting complaints (18 categories)[43]. To focus on predicting the acute service demands, we will exclude CTAS Level 5 visits that were classified as non-urgent cases with minor or mild conditions.

The ED visits will be stratified by relevant ICD codes. Relevant ICD code selection was based on the literature related to EHEs and their associated health outcomes. Outcomes of interest determined from the literature review were heat related illnesses, pneumonia, diabetes mellitus, acute renal failure, ischemic heart disease, and relevant neurocognitive disorders. ICD-10 and analogous ICD-9 codes for these outcomes are recorded in Appendix S1. For ED visits where there are multiple diagnoses, the primary ICD codes will be selected, with the secondary code being used when the primary code is not one of our selected outcomes. This has been shown to produce stronger associations where underlying diagnoses were related to the EHE[31].

4.4. Analysis

A detailed flowchart illustrating our data analysis process plan can be found in Appendix S3.

4.4.1. Exploratory Data Analysis (EDA)

The EDA will be separated into 3 sections. The first section will compare similarities in time. Dynamic time warping (DTW) is a technique measuring the similarity between two time series in which the starting and ending points are aligned to some points, and then each point along the two series is matched in sequential order to account for time distortions or shifting of similar patterns[44]. Internally, for each CHSA or hospital, we will assess, locally, the alignment of pairwise time series of different variables. Meanwhile, DTW can also be used as a distance metric in clustering to identify CHSAs or hospitals with high similarities in corresponding time series of environmental and health indicators. The K-means algorithm will be applied to compute the cluster centroids based on the DTW distance and optimize the clustering output.

The second section will tackle descriptive statistics of the study cohort generated based on individual-level demographic characteristics from MSP patient registration file. The attributes include rurality (i.e., metro, urban, rural), after-tax income quintile (1-5), administrative sex (Male/Female), age group (20 - 39 years, 40 - 59 years, 60 - 79 years, 80+ years), and nearest Health Authority (Interior, Fraser, Vancouver Coastal, Vancouver Island, Northern). We will use a modified Poisson regression to compare the relative risk of an ED visit during any EHE within the study period for each level of the demographic variables compared to the baseline level.

Lastly, the third section will seek to describe the number of additional disease-specific ED visits. CTAS levels 1-4 indicate illness severity within these groups. We will conduct a Mann-Whitney U test comparing the differences in overall ED visits during EHEs to baseline periods. We will repeatedly apply this test for each of the ICD codes in Appendix S1 and CTAS severity levels as the second stratification. The Mann-Whitney U test is a non-parametric with less stringent assumptions to favor for the small sample size of the rarer health outcomes[16].

4.4.2. Pre-Processing

The EDAs will help us to perform feature selection and inform the approaches for the feature engineering process: i) DTW-based time series K-means clustering indicates the presence of locality effects and if the environmental features are associated with ED visits; ii) Poisson regression models tell which levels of the demographic features have the higher need for ED services during EHEs; iii) statistical tests on descriptive tables will suggest the relevance of each ICD code as the outcome in modelling ED visits.

For feature engineering of time series prediction, lagged features are created per predictor and the outcome variable itself. Through inspecting the auto-correlation function and partial auto-correlation function of ED visits, we can determine the lag and seasonality effects of previous ED visits useful for forecasting. For climate and air quality features, we will visualize and test the correlation between the current ED visit and their lagged observations. Each feature can have different sized lag windows. Local health administrative features (e.g., triage statistics, ED diagnoses, and MSP registrant demographics) in the prior year or over a multi-year period will be included as static features.

To capture the long-term effects, time series decomposition will be used to extract the seasonality, trend, and residual components. Alternatives that may be explored include spline smoothing or exponential smoothing averages. We will extract the mean and maximum aggregating the hourly environmental observations to sliding windows of 6 hours as our prediction intervals.

4.4.3. Machine Learning Model

To compile the training dataset, it is anticipated that the number of EHE days will be much lower than the non-event days and each event will be of varying length/duration. Our training records will contain all single time steps (6 hours) during the defined EHEs. To balance the ratio between event data and non-event data, we will randomly sample episodes from non-event days with the length/duration of each episode drawn from the distribution of length/duration of the event days (Appendix S4). For each episode, the lag window of input features will necessarily extend before the starting time step of the episode for training and to predicting.

For validation on the time series, event and non-event episodes are partitioned into equal-length sections (see Appendix S5). We will evaluate the performance by forecasting the ED visits over the next 6 hours, 12 hours, until 72 hours. The predicted output of ED visits for the next time step (6 hours) will be re-used as the input in the sliding lag window for predicting the output at 12 hours. This is recursively done until the maximum prediction time step (i.e., 72 hours) (Appendix S6).

Three types of models will be evaluated, including linear, ensemble, and deep learning algorithms. The linear method proposed is Poisson regression model. Regularization and random-effect features will be included to enhance the predictability of the model. For the ensemble method, Gradient Boosting (GB) could provide efficient implementations[45]. Finally, the deep learning model will comprise of a recurrent neural network (RNN) embedding extractor on the lagged environmental and health features, connected to an attention layer, then passed to the feed-forward (FC) layers concentrating the static features. The final output is the count of total ED visits, which will then be transformed into classes of no exceedance (i.e., 0%), 5%, 10%, and more than 10% exceedance against the 6-hour median of ED visits. Furthermore, performance evaluation will be reported, including 1-step (6-hour) to 12-step (72-

hour) accuracy, precision, recall, and F1-score. This will help us examine the change of model performance over immediate to longer periods. Furthermore, to acknowledge a baseline, we will set up and use a Hidden Markov Model (HMM).

As we are also interested in the ICD code-specific exceedance levels, we will train another model analogous to a multi-label classification problem predicting multiple outputs per ICD code label at each step. To tackle this, we will adapt our model structure to that of the Attention-aware Extreme Multi-label Classification (AttentionXML) model (Appendix S7)[46]. We may also try more advanced attention mechanisms, such as used in Transformer models. The attention output (weightings) will be shared for independent block of FC layers specific for each ICD code, improving computational efficiency.

For model interpretability, we can understand the effects from the regression coefficients of the linear model and identify the important predictors from the variable importance of the GB model. For the NN, intermediate layer weightings, typically the attention layer output, can be extracted and examined with explainable AI tools like LIME (local interpretable model-agnostic explanations).

5. Budget and Timeline

The proposed project will take place over a 3-year period, with an estimated budget of 205,000 CAD (Table 1). A more detailed view of the proposed timeline can be found in Appendix S8.

Estimated 3-year project for the proposed project:

- Research Ethics Board (REB), popdataBC access approval, and data collection – *Year 1 Fall to Year 1 Spring*
- Exploratory Analysis – *Year 1 Spring to Year 1 Summer*
- Predictive Modeling – *Year 1 Summer to Year 2 Summer*
- Manuscript Preparation and Knowledge Translation –*Year 1 Summer to Year 3 Spring*

Table 1. Budget Justification

Expense	Time Period Expense Needed	Amount	Justification
popdataBC Data Access Fee	Year 1	$15,000	PopData BC offers students performing projects using their services a fee waiver, which we will exploit. However, the health data that we are requesting from British Columbia requires an overall access fee to be paid. Any linkage to other database data (e.g., NACRS) is included in this data access fee.
Computing Requirements	Year 1	$5,000	To have the proper computing capacity to handle such a large amount of health data, purchasing a GPU with additively 32GB VRAM in this price range would be able to handle all the computational requirements needed.
Student Trainees (4 students)	Year 1 & Year 2	$40,000 per year ($80,000 total)	4 graduate students will be working on completing this project staggered over the course of 3 years. The Dalhousie University Faculty of Graduate Studies requests a minimum of about $10,000 per year for at least a Master's-level student stipend.
Conference Fees	Year 1 & Year 2	$5,000 per year ($10,000 total)	International Society for Environmental Epidemiology (ISEE) (4 days): $510 registration; $720 for flights (estimate for flight to Atlanta, Georgia (where conference takes place in 2025)); $800 for accommodations ($200 x 4 nights); $150 for ground transportation; meals are in conference registration. ISEE Conference – Future Conferences (iseepi.org) Canadian Society for Epidemiology and Biostatistics (CSEB) (3 days) for 2 people: $1000 for registration ($500 x 2 people); $600 for flights ($300 x 2 people) (estimate for flight to Montreal, Canada (where conference takes place in 2025)); $300 for meals ($150 x 2 people ($50 per diem x 3 days)); $600 for accommodations ($200 x 3 nights; both people will stay in same accommodation); $300 for ground transportation ($150 x 2 people). CSEB-SCEB Conference 2025 (cseb.ca) International Conference on Emergency Medicine (ICEM) (5 days): $580 for registration ($290 x 2 people); $500 for meals ($250 x 2 people ($50 per diem x 5 days)); $300 for ground transportation ($150 x 2 people); $2,200 for flights ($1,100 x 2 people (estimate for a round-trip international flight to Hamburg, Germany in 2026)); $1,000 for accommodations ($200 x 5 nights) (both people will stay in same accommodation). International Federation for Emergency Medicine – Upcoming ICEMs (ifem.cc/about_icem)
Journal Publication Fee	Year 2	$5,000	Open access publishing fee for The American Journal of Emergency Medicine or The Journal of Climate Change and Health. Price for open-access publication is $3,540USD (excluding taxes) = $4,857CAD @ 1.37:1 (exchange rate as of June 18th, 2024) ScienceDirect | Open Access Information (sciencedirect.com)
Total		$205,000	

6. Ethics

This study will undergo ethics review at the Dalhousie Research Ethics Board for secondary use of information for research. Individual-level linked data on patient diagnoses and demographics will be de-identified to minimize risk to participant privacy. Since relevant outcomes to EHEs are more likely to affect older populations, children are less likely to benefit from the results of this study. Since the linkage of individual level data poses privacy concerns with respect to presentation of patient characteristics and rare outcomes in children, there is less benefit than the foreseeable risk in accordance with Article 4.6 of the TCPS 2 (2022)[47].

7. Discussion

7.1. Potential Challenges and Limitations

While the spatial alignment of CHSAs with hospital locations is likely to reflect where the majority of local EHEs and resultant ED visits occurred, there are many reasons residents may choose to access an alternate ED than that within their CHSA. Local weather conditions are also variable within these areas due to topographic features providing shade and urban heat islands that re-emit infrared radiation at a greater rate than natural landscapes. It is possible that heat contributes to ED visits not collected as part of our selected ICD codes. Additionally, visits are required to have been coded with the appropriate ICD code to be included in our outcomes.

A strength of the study is that these outcomes also represent a generalizable selection taken from a literature review that considers alternate study designs and contexts. By furthering our understanding of how EHEs affect specific conditions, health system planners can consider both the total ED visit counts predicted by the model and the proportion with conditions that may require specialist staffing and urgent referrals to psychiatry, urology, nephrology, cardiology, or internal medicine.

7.2. Future Work

There are many great opportunities to expand upon the proposed project once complete. The future work we envision would enhance the applicability, robustness, and scalability of our modeling include, firstly, proposing implementation of our forecast modeling across *all* hospitals in British Columbia. This comprehensive roll-out would allow for the testing of the proposed model's performance in diverse healthcare settings, as well as evaluate overall health outcome improvements that have occurred due to the implementation of our system. Secondly, our long-term goal is to expand our forecasting system to other provinces in Canada, with the hopes of eventual development of a national-scale predictive tool. Expansion of the tool to such a large scale would facilitate proactive healthcare resource allocation and management across Canada during EHEs. To accomplish this, extensive testing will be needed to adapt modeling to different provincial and regional healthcare systems and climatic conditions. Finally, we have hopes to enhance and expand the model's predictive capabilities by focusing on both specific medical conditions that are most susceptible to extreme heat, as well as more general medical conditions. By identifying and targeting such medical conditions, our model could provide more precise forecasts and enable more targeted and effective healthcare intervention, as well as ensuring that the necessary resources and staff are on hand before, during, and after periods of extreme heat.

8. Knowledge Translation

As this research aims at improving our ability to accurately predict and estimate ED visits and resources needed over periods of extreme heat events, there are a diverse group of stakeholders that need to be involved to effectively communicate and utilize our research. Therefore, a very integrated approach is crucial to maximize the impact and applicability of our forecast modeling and to ensure continuous exchange of information, ideas, and feedback throughout every stage of the process. This project's primary relevant stakeholders include hospital administrators, public health agencies (e.g., B.C. Centre of Disease Control), clinicians, and academic researchers already actively involved in similar research (e.g., University of British Columbia's (U.B.C.'s) HEAL cluster (Climate Change Health Effects, Adaptation, and resiLience)). Furthermore, our project will partner with hospital groups, such as Fraser Health, to perform proper test implementations to validate our models in real-world settings. A diagram summarizing our Knowledge Translation Plan is illustrated in Appendix S9.

Moreover, the project team will engage with other experts in relevant interdisciplinary fields, such as environmental and meteorological modeling research groups, health data modeling researchers, and health administrators, over the course of the project through an assortment of engagement activities. Engagement activities will include presentations and meetings with local groups, such as the Canadian Climate Institute and U.B.C. HEAL, participation in relevant conferences, and networking with researchers at other institutions will be prioritized to enhance the scope and impact of our research. The team will also explore online engagement with researchers from relevant fields using mediums, such as Twitter and ResearchGate, to share and discuss ideas and troubleshooting strategies.

Upon project completion, our findings will be written up in a manuscript and submitted to a relevant peer-reviewed journal, such as *The American Journal of Emergency Medicine* or *The Journal of Climate Change and Health*. To ensure broad accessibility and prevent any financial barriers of access, our team will opt to make our results open-access. In addition, we will promote our research through various channels, including creating and sharing an easy-to-understand video abstract and full-text links that will be disseminated via our social media platforms (e.g., Instagram, Twitter, ResearchGate), as well as our stakeholders' online networks, to reach a wider audience. Our results will also be presented at both national (e.g., Canadian Society for Epidemiology and Biostatistics Conference) and international (e.g., International Society for Environmental Epidemiology Conference) conferences to further engage stakeholders, help with implementation, and help further shape next steps.

Finally, although for privacy and confidentiality reasons, our team will only share pieces of our code, such as our exploratory analyses, and a sample of de-identified data via GitHub that is deemed eligible to be shared for public use, a public dashboard will be developed that can be viewed openly online and can be easily integrated with pre-existing heat dashboards, such as the B.C. Heat Alert and Response System (H.A.R.S.), to offer comprehensive and accessible data to the public. A sample of the dashboard's design is included in Appendix S10. Therefore, by engaging stakeholders throughout the research process and employing a variety of dissemination strategies, we aim to ensure that our findings are not only accessible but also actionable, leading to improved health outcomes and more efficient preparation over EHEs.

9. References

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10. Appendix

Table S1. Relevant Health Outcomes from Literature Review

	ICD-10 Code	ICD-9 Code	VCH Report	Chen et al.	Fuhrman et al.	Knowlton et al.	Clark et al.	Wettstein et al.	Beugin et al.
Heat Related Illnesses	T67	276, 992	X	X	X	X	X	X	X
Pneumonia	J18	480–486		X*	X*		X	X	X
Diabetes mellitus	E08-E13	249-250		X*	X*	X	X	X	X
Acute Renal Failure	N17	584	X	X	X	X	X	X	X
Ischemic Heart Disease	I20-I25	410–414		X	X*	X*		X*	
Neurocognitive disorders	F20-F48	290–319			X*		X		X

*increase in ED visits related to diagnosis, $p>0.05$

Table S2. Summary of Relevant Literature Investigating Associations Between Extreme Heat and Health

Studies Investigating Extreme Heat and Health Associations	Exposure Variables Measured	Outcome(s) Measure	Geographic Region	Disease-specific analysis	ICD-10	ICD-9	Time Scale	Sample Size
Nori-Sama et al. (2022)[25]	County-specific daily maximum ambient temperature; Extreme heat defined as 95th percentile of the county-specific warm-season temperature distribution	Daily incidence rate (IR) of cause-specific mental health diagnoses; incidence rate ratios for association between daily temperature and IRs of ED visits	United States	Mental Health and Mental Disorders	*Note*: Used CCS codes for grouping		January 1, 2010 to December 31, 2019	3,496,762 ED visits among 2,243,395 unique individuals (adults, 18+ years)
				Mental Health	650-652, 654, 655, 657-662, 670			
				Substance use disorders	660, 661			
				Anxiety, stress-related, and somatoform disorders	650, 651			
				Mood disorders	657			
				Schizophrenia, schizotypal, and delusional disorders	659			
				Self-harm	662			
				Childhood-onset behavioral disorders	652, 654, 655			
				Miscellaneous	670			
				Adult personality and behavior disorders	658			
Stingone et al. (2019)[26]	Closest stationary PM2.5 levels; meteorological data (daily temperature, dew point, wind speed,	Relative excess risks due to interaction (RERI) of Congenital Heart Defects	United States	Congenital Heart Defects		745.00, 746.88, 745.01, 745.10, 745.11, 745.12, 745.18, 745.185,	January 1, 1999 to December 31, 2007	4,033 controls; 2,632 cases

	etc.); EHE defined as maximum ambient temperature in upper 95th percentile for at least 2 consecutive days or upper 90th percentile for 3 consecutive days					745.186, 745.188, 745.189, 745.20, 747.31, 746.020, 745.30, 745.31, 745.32, 745.33, 745.38, 745.485, 745.487, 745.685, 745.486, 745.490, 746.880		
Lee et al. (2023)[48]	No exposure data used, solely compared deaths between 2021 EHE and deaths during same time period in other years	Mortality and prevalence of chronic diseases (odds ratios)	British Columbia, Canada	Acute Myocardial Infarction Angina Asthma Chronic Kidney Disease Chronic Obstructive Pulmonary Disease Dementia Depression Diabetes Epilepsy Gout Heart Failure Transient Ischemic Attack Hypertension Ischemic Heart Disease	Does not specifically mention the ICD codes for the chronic diseases analyzed		Compared deaths between 25 June to 2 July 2021 to deaths in 25 June to 2 July in 2012 to 2020	1,649 deaths during 2021 EHE and 6,700 deaths during typical weather period

				Ischemic Stroke				
				Osteoarthritis				
				Osteoporosis				
				Parkinsonism				
				Rhematoid arthritis				
				Schizophrenia				
				Substance use disorder				
Arrighi et al. (2024)[1]	Climate Shift Index (CSI); Defines heatwave as unseasonably high temperatures over a large geographic area for a prolonged period (3+ days) or media reports at least 10 heat-related deaths or major disruptions to critical economic sectors	Probability ratios for triggered heat events	90 different countries across all continents	Death	No ICD codes were mentioned		May 15, 2023 to May 15, 2024	Used estimated population sizes of each country analyzed
Basu et al. (2012)[49]	Mean apparent daily temperatures, ozone concentrations	ED visit utilization	United States (California)	Cardiovascular diseases		390-459	Warm seasons (2005-2008)	1.2 million ED visits
				Respiratory illnesses		460-519		
				Diabetes		250		
				Dehydration		276.51		
				Heat illness		992		

	, carbon monoxide, nitrogen dioxide, sulfur dioxide, daily average PM2.5 levels			Intestinal infectious diseases		001-009		
				Acute renal failure		584		
Rhea et al. (2012)[50]	Maximum daily ambient temperature	Proportion of heat-related ED visits compared to total ED visits	United States (North Carolina)	Heat-related illnesses		992.xx, E900, E900.0, or E900.9, 780.2, 780.4, 780.79, 780.99, 276.51, 401.0, 401.1, 401.9, 305.1, 787.01, 787.02, 787.91	2009-2010 temperatures in season (May 1 to September 30)	7,242 heat-related ED visits
				Diabetes mellitus		250.0-250.03		
Lippmann et al. (2013)[51]	Daily mean temperatures	Daily ED visit incidence rates and IRRs	United States (North Carolina)	Heat-related effects		992.xx	2007-2008	2,539 ED visits with heat-related illness as primary diagnosis
Hess et al. (2014)[52]	Only looked at May-	ED visit utilization	United States (national data)	Acute heat illness		992.0-992.9, E900	2006-2011 (May-	326,497 cases of heat-

	September periods						September periods)	related ED-visits in the study period (average of 65,299 ED visits for summertime acute heat illness per year)
Wu et al. (2014)[53]	Only looked at warm seasons	ED visit utilization	United States (national data)	Heatstroke		992.0	2009-2010 Warm season	8,251 ED visits for heatstroke (approximately 4,100 ED visits each year); 101,995 ED visits for unspecified heat exhaustion and 39,142 ED visits for other heat-related illnesses
Hardaur-Morano et al. (2015)[54]	Only during specified time periods	ED visits, hospitalizations, and deaths	United States (Florida)	Heat related illnesses	T67-T67.9; X30; W92	992-992.9; E900.0; E900.1, E900.9; E000.0,	2007-2012 (May to October periods)	8,315 occupational heat related illness ED visits

						E000.1, E800–E807; E830–E838; E840–E845; E846, E849.1–E849.3		documented; 23,981 non-work-related HRI cases treated in the ED, 4816 HRI hospitalizations, and 139 HRI deaths; majority of non-work-related HRI ED visits (83.9%; n = 22,669), hospitalizations (86.1%; n = 4582), and deaths (85.4%; n = 135) were observed between May and September
				Mortality	All diagnosis codes contributing to cause of death fields were used			
Zhang et al. (2015)[55]	Average max, mean, and minimum temperatures, compared to 3.7, 2.5, and >1.4°C in	All-cause mortality and ED visits; excess risk in ED visits; excess mortality risk	United States (Texas)	Mortality (all cause)	Restricted to internal causes (ICD-10 codes below S) or external causes due to extreme		Heatwave in 2011 (August 2-30); May 1-September 30 period for 2007-2011 as reference period	2,064 all cause daily ED visits during heatwave (compared to 1,786 daily

	reference period 2007-2010; Ozone measurements				heat (X30, T67)			ED visits during reference period) and 52 daily all cause mortality events during heatwave (compared to 51 during reference period)
				All cause ED visits		Internal causes (codes less than 800); causes due to extreme heat (992, E900)		
Henderson et al. (2021)[17]	Compared 2021 EHE to same period in other years	Number of deaths	British Columbia, Canada	Heat-related deaths	No ICD codes provided		Compared 2021 EHE to same period in other years	1,630 deaths occurred during the 2021 EHE, meaning 740 more deaths occurred than would normally be expected during a summer period
Clark et al. (2024)[16]	Daily Maximum Temperatures	Daily ED visits	Greater Vancouver Area, Canada	Heat related illnesses	TA7	276, 992	June 4th, 2021 to July 29th, 2021	ED visits (n=36,432) Hospitalizations (n=18,624)
				Pneumonia	J18	480-486		
				Diabetes Mellitus	E08-B13	249-250		
				Acute Renal Failure	NI7	584		

				Neurocognitive Disorders		F20-F48	290-319		
Zhao et al. (2021)[27]	Average daily mean, minimum, and max temperatures	Average excess deaths due to non-optimal temperatures	Global study (43 countries)	All-cause deaths		A00-R99	0-799	January 1, 2000 to December 31, 2019	A total of 130,217,521 deaths used in model; Globally, 5,083,173 deaths were associated with non-optimal temperatures per year (489,075 excess deaths were heat-related)
Pillai et al. (2014)[28]	Daily maximum and minimum temperatures; EHE defined as at least 2 consecutive days above 99th percentile daily max temperature value	ED visits	United States (Georgia)	Heat related illness			992.0-992.7; E900.0	2002-2008 (May-September)	13,784 individuals with heat-related illness ED visits; of those visits, 1,223 coincided with a defined EHE and was associated with increased odds of hospitalization (OR 1.42, *p*<0.001)
				Comorbidities	Behavioral disorders		290-319		
					Diabetes mellitus		250		
					Fluid and electrolyte disorders		276		
					Cardiovascular disorders		390-398; 402, 404-429, 440-448		
					Cerebrovascular disorders		430-438		
					Respiratory disorders		460-519		

					Renal disorders		580-589		
Fuhrmann et al. (2016)[23]	3 Extreme Heat Events	ED visits	United States (North Carolina)	Heat related illnesses	TA7	276, 992	Jan 1, 2007 to Jan, 2011	ED Visits: n=13040
				Pneumonia	J18	480-486		
				Diabetes Mellitus	E08-B13	249-250		
				Acute Renal Failure	NI7	584		
				Ischemic Heart Disease	I20-125	410-414		
				Neurocognitive Disorders	F20-F48	290-319		
Knowlton et al. (2009)[24]	Comparing heatwave period with reference period	Hospitalizations and ED visits; excess morbidity and rate ratios	United States (California)	All internal causes		001-799.9	Heat wave of 2006 (15 July-1 August) compared to reference period (8-14 July and 12-22 August 2006)	501,951 ED visits during heatwave period (compared to 485,785 visits during reference period); 16,166 excess ED visits and 1,182 excess hospitalizations statewide; Heat-related ED visits increased (RR=6.30)
				Diabetes mellitus		250		
				Disorders of fluid and electrolyte balance		276		
				Cardiovascular diseases		390-398, 402, 404-429, 440-448		
				Acute myocardial infarction		410		
				Cerebrovascular diseases		430-438		
				Respiratory illnesses		460-519		
				Nephritis and nephrotic syndrome and nephrosis		580-589		
				Acute renal failure		584		
				Heat-related effects		992		
Poumadère et al. (2005)[9]	Compared 2003 EHE to reference period	Excess mortality	France	Heat-related causes of death on death certificates	No ICD codes provided		2003 European EHE (August) compared to same time of	An excess of 14,947 deaths occurred

							year in other years	between August 4 and 18, 2003; greatest increase in mortality was due to causes directly attributable to heat: dehydration, hyperthermia, heat stroke
Jiang et al. (2021)[30]	Hourly ambient air (dry-bulb) temperature, dew point temperature, and apparent temperature	ED visits (relative risk estimates)	United States (Georgia)	Internal causes		001-799	1993-2012	A total of 11,004 daily ED visits were estimated for all diseases included during May-September from 1993-2012
				Heat illness		249, 250		
				Ischemic stroke		276		
				Fluid and electrolyte imbalances		390-459		
				All renal disease		401-405		
				Acute renal failure		410-414		
				All circulatory system disease		410		
				Hypertension		428		
				Myocardial infarction		433-437		
				Congestive heart failure		580-593		
				Ischemic heart disease		584		
				Diabetes		992.5		
Winquist et al. (2016)[31]	Daily minimum, maximum, and average temperature, dew-point temperature,	Daily ED visit counts; rate ratios	United States (Georgia)	All internal causes		001-799	January 1, 1993 to December 31, 2012	Total of 9,856,015 ED visits during warm seasons, of which 6,994,110
				Heat illness		992		
				Fluid/electrolyte imbalances		276		
				Renal disease		580-593		
				All circulatory system disease		390-459		
				Nephritis and nephrotic syndrome		580-589		

	apparent temperature, wind speed, average barometric pressure, total precipitation, and daily major ambient air pollutant concentrations			Intestinal infections		001-009		indicated internal causes and 8,594 indicated heat illness
				Hypertension		401-405		
				Ischemic heart disease		410-414		
				Dysrhythmia		427		
				Cardiorespiratory-related problems		428, 460-519, 480-486, 491-492, 496, 493		
				Ischemic stroke		433-437		
				Diabetes mellitus		250, 249		
Wettstein et al. (2024)[21]	Maximum daily temperatures	ED visits and inpatient admissions	United States (Washington)	Heat related illnesses	TA7	276, 992	2021 EHE (June 26-28)	Total of 2103 ED visits included; 909 ED visits and 247 inpatient admissions across 3 hospitals during EHE
				Pneumonia	J18	480-486		
				Diabetes Mellitus	E08-B13	249-250		
				Acute Renal Failure	NI7	584		
				Ischemic Heart Disease	I20-125	410-414		
Chen et al. (2017)[22]	Maximum, minimum, and average daily temperatures, apparent temperature, and dew-point temperature			Same diagnostic outcomes as Winquist et al. (2016)	Same ICD codes as Winquist et al. (2016)		January 1, 1993 to December 31, 2012	Total of 9,856,015 ED visits, with 6,994,110 indicating internal causes; overall mean daily count was 2,286, with overall mean daily

								counts of cause-specific ED visits ranging from 6 (acute renal failure) to 622 (all circulatory diseases)

Figure S3. Flowchart depicting the data processing steps that will be taken for data analysis

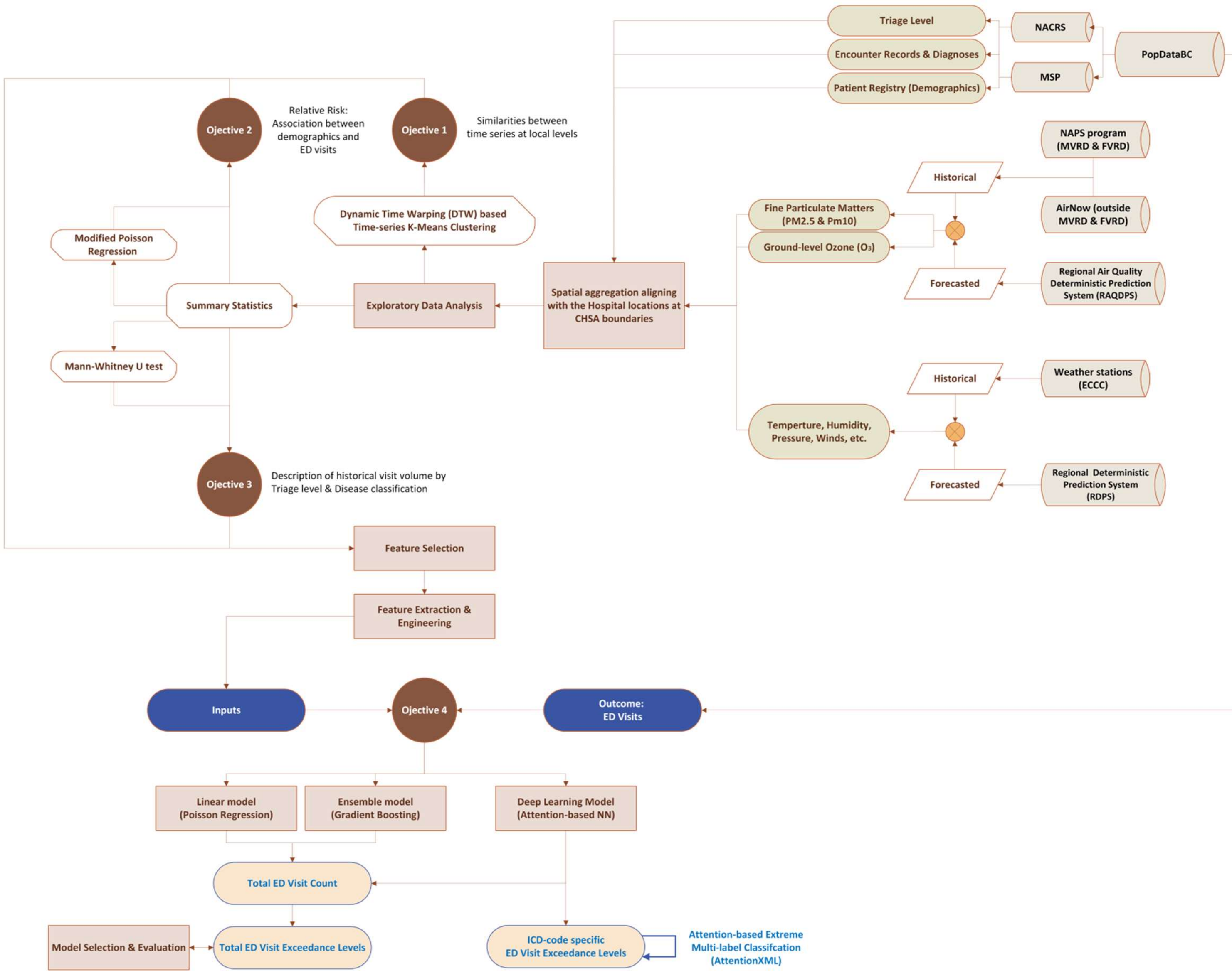

Figure S4. Illustration of the ideas of extracting EHEs and non-EHEs as the training dataset

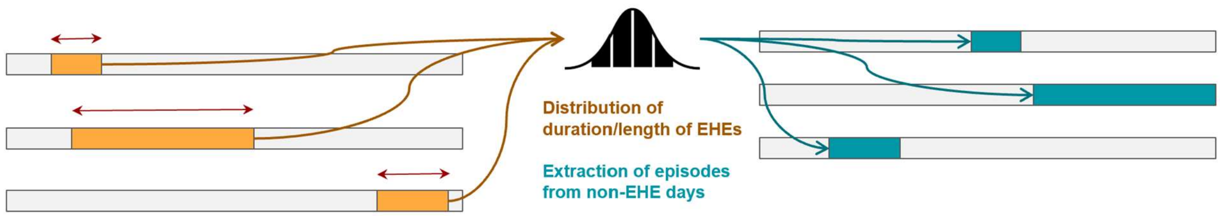

Figure S5. Illustration for time-series splitting in cross-validation of the proposed machine learning model training process

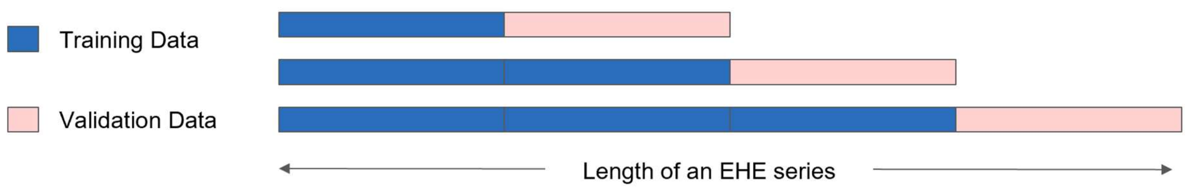

Figure S6. Illustration of the multi-step predictions

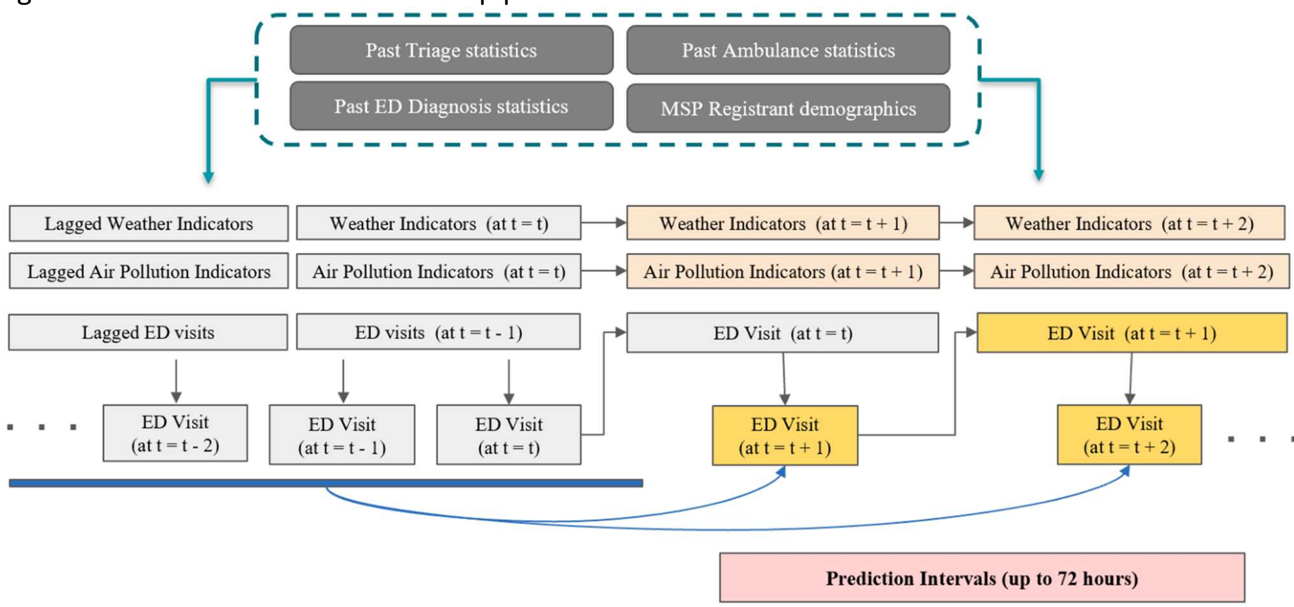

Figure S7. Model Architecture of AttentionXML, originally designed for multi-label topic recognition (You et al., 2019)[46]

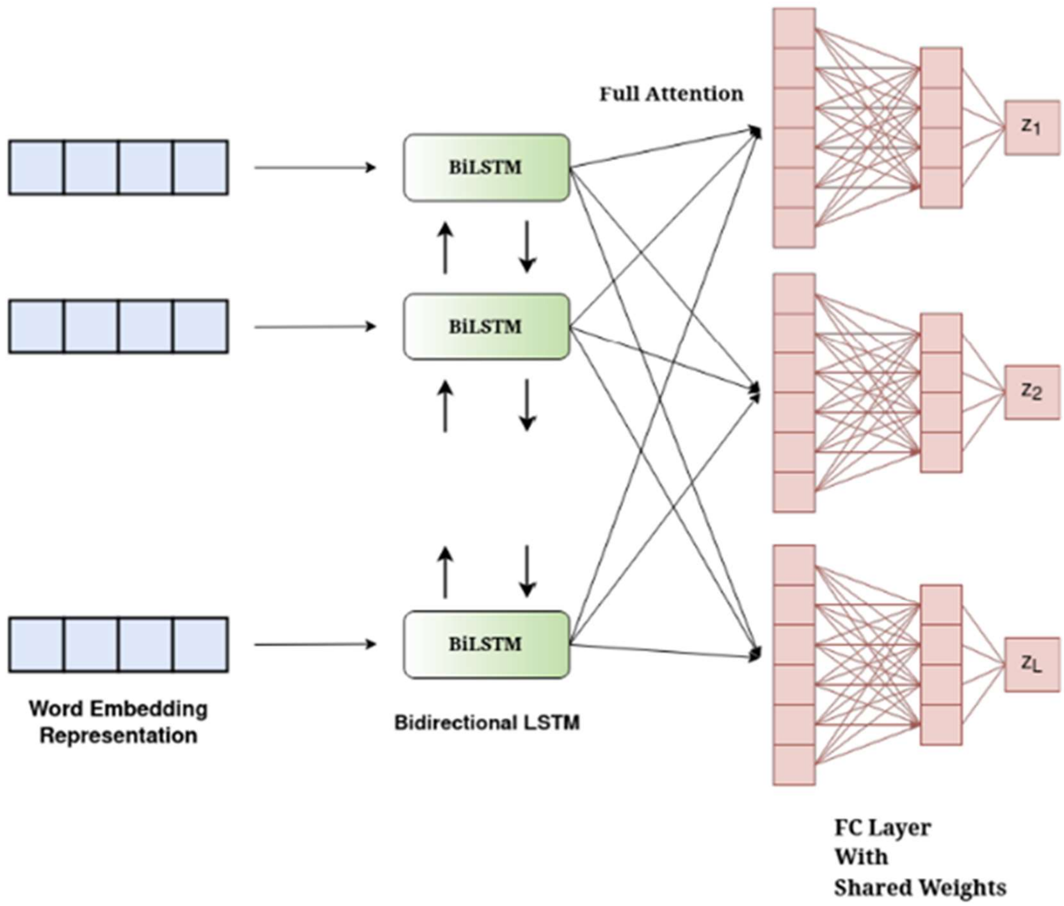

Table S8. Detailed Timeline of Proposed Project

		Y1: Fall	Y1: Spring	Y1: Summer	Y2: Fall	Y2: Spring	Y2: Summer	Y3: Fall	Y3: Spring
REB Approval		■							
popdataBC Access Approval: Health Data Collection		■	■						
Environmental and Socio-Demographic Data Collection		■	■						
Exploratory Analysis	**Association between time series per Community Health Service Area (OBJ1)**		■	■					
	Visualization of local population demographics and accessibility (OBJ2)			■					
	Visualization of patient-level demographic and health problems (OBJ3)			■					
Feature Selection and Engineering			■	■					
Predictive Modeling	**ED Visit Exceedance Levels Relative to Daily Median (OBJ4)**			■	■				
Predictive Modeling	**ED Visit Exceedance Levels Based on ICD-coded Diseases/Diagnosis**					■	■		
Manuscript Writing/Publishing to Journal(s)				■			■		
Conferences, Speaking/Community Meetings				■			■		
Implementation in Potential Hospitals								■	
Evaluation of In-Hospital Performance									■

Figure S9. Figure Describing Integrative Knowledge Translation Plan (adapted from Hartling et al. (2021))

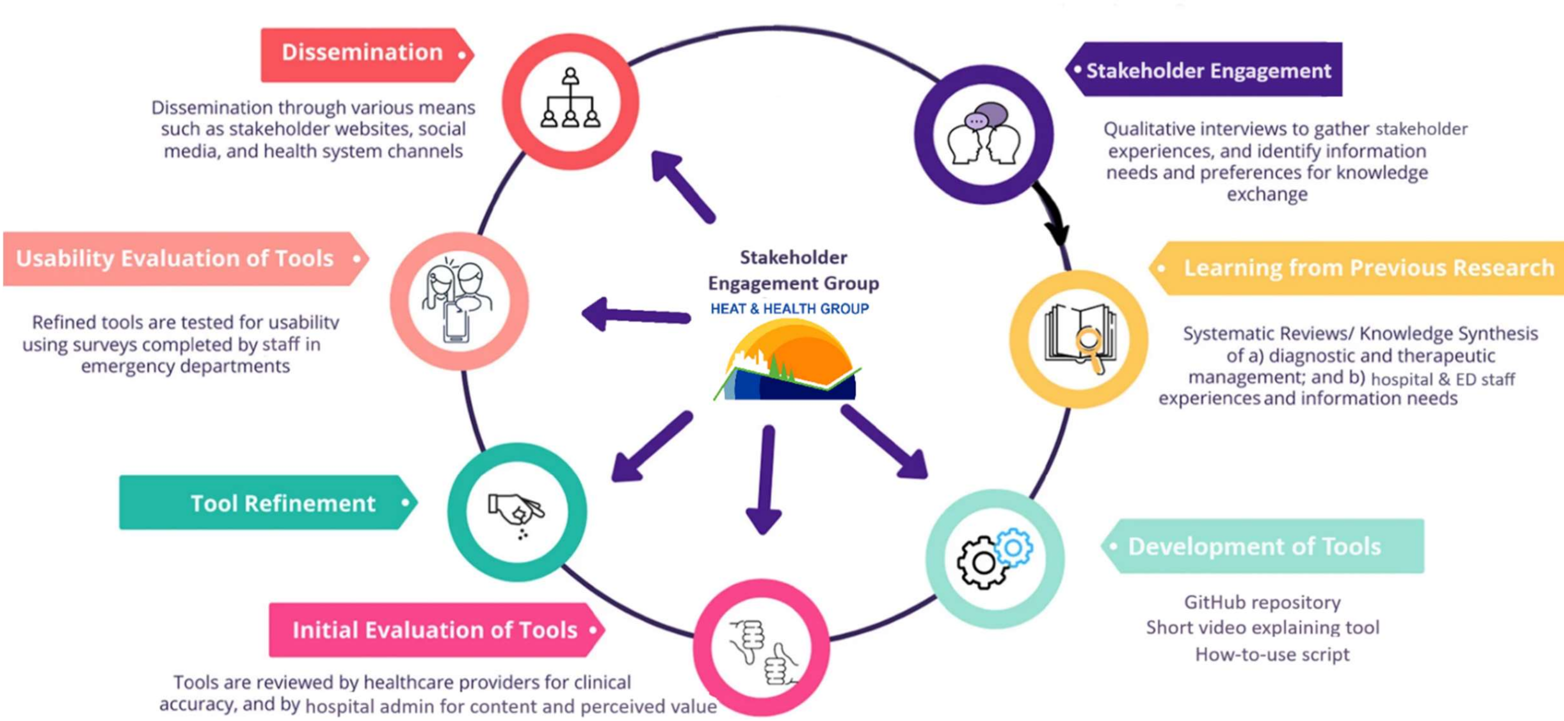

Figure S10. Figure Depicting Example of What Resultant Online Dashboard For Project Could Look Like (adapted from Murtas et al. (2022))