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The Daily Patterns of Emergency Medical Events

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The Daily Patterns of Emergency Medical Events

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Abstract

This study examines population level daily patterns of time-stamped emergency medical service (EMS) dispatches to establish their situational predictability. Using visualization, sinusoidal regression, and statistical tests to compare empirical cumulative distributions, we analyzed 311,848,450 emergency medical call records from the U.S. National Emergency Medical Services Information System (NEMSIS) for years 2010 through 2022. The analysis revealed a robust daily pattern in the hourly distribution of distress calls across 33 major categories of medical emergency dispatch types. Sinusoidal regression coefficients for all types were statistically significant, mostly at the $p < 0.0001$ level. The coefficient of determination (R^2) ranged from 0.84 and 0.99 for all models, with most falling in the 0.94 to 0.99 range. The common sinusoidal pattern, peaking in mid-afternoon, demonstrates that all major categories of medical emergency dispatch types appear to be influenced by an underlying daily rhythm that is aligned with daylight hours and common sleep/wake cycles. A comparison of results with previous landmark studies revealed new and contrasting EMS patterns for several long-established peak occurrence hours–specifically for chest pain, heart problems, stroke, convulsions and seizures, and sudden cardiac arrest/death. Upon closer examination, we also found that heart attacks, diagnosed by paramedics in the field via 12-lead cardiac monitoring, followed the identified common daily pattern of a mid-afternoon peak, departing from prior generally accepted morning tendencies. Extended analysis revealed that the normative pattern prevailed across the NEMSIS data when re-organized to consider monthly, seasonal, daylight-savings vs civil time, and pre-/post- COVID-19 periods. The predictable daily EMS patterns provide impetus for more research that links daily variation with causal risk and protective factors. Our methods are straightforward and presented with detail to provide accessible and replicable implementation for researchers and practitioners. [284 words/300 word max.]

The Daily Patterns of Emergency Medical Events

Much research in social sciences, medicine, public health, epidemiology, and biology is devoted to understanding circumstances affecting human health. The present study examines time-stamped emergency medical service (EMS) distress calls. For several decades, daily patterns have been suggested for specific medical events. Most notably, acute myocardial infraction (*heart attack*), cerebrovascular accident (*stroke*), and sudden cardiac arrest/death have long been perceived as prevalent in the morning (Cohen et al., 1997; Elliott, 1998; Muller et al., 1985, 1987; Muller, 1999; Rocco et al., 1987; Thakur et al., 1996; Willich et al., 1987). Several reviews and studies, have supported or confirmed before-noon occurrence peaks (Akkaya-Kalayci et al., 2017; Buurma et al., 2019; Klerman, 2005), while others failed to replicate a morning tendency (Faramand et al., 2019; Ni et al., 2019; Tripathi et al., 2020; Vencloviene et al., 2017); see Tables 1 and 2.

The analysis in this paper is not the first attempt to describe or predict general rhythms for medical emergencies. Prior research modeled ambulance dispatch volumes (Ohshige, 2004; Vile et al., 2012), analyzed EMS events (Jasso et al., 2007; Setzler et al., 2009), and studied hospital emergency department visit patterns (Ferrazzi et al., 2018; Manfredini et al., 2002; McCarthy et al., 2006). Our analysis expands this body of literature by deriving hourly distributional models from a voluminous amount of time-stamped data. Our analysis is like that of previous approaches that organize medical emergency patterns by specific type (Ferrazzi et al., 2018). In our analysis, daily patterns are derived from the hourly occurrence distribution based on the specific time-stamped dispatch events, which are organized by chief complaints and priority symptoms.

Several recent time-of-day studies point to the potential for better outcomes in terms of human health and well-being. A number of authors suggest pharmacological intervention, usually aligning dosing with specific times of day and/or possible physiological causes or risks (Akkaya-Kalayci et al., 2017; Buurma et al., 2019; Cohen et al., 1997; Elliott, 1998; Muller et al., 1985; Muller, 1999; Pavlova et al., 2012; Rocco et al., 1987). Others posit systemic or individual behavioral interventions, such as aligning youth suicide counseling sessions to coincide with evening patterns of social media rumination and suicide attempts (Allegra et al., 2001; Dutta et al., 2021), recommending a review of carbohydrate sufficiency in hospital meals to counter timing variations of in-patient hypoglycemic events (Kerry et al., 2013), or recommending time-of-day posture control findings to optimize return-to-play after sports injuries (Gribble et al., 2007). (See Tables 1 and 2 for summaries of authors' suggested methods of prevention.) Based on found EMS daily patterns and contrasting with previous studies, our results suggest that much further research is needed regarding causes, risks, and protections for each medical emergency category, including the investigation of reasons for consistency in the daily pattern among dissimilar event types.

To date, no researchers have recognized the broad existence of a common daily pattern for medical emergencies, nor confirmed patterns for specific cases using a national data-set as extensive as NEMSIS. The aims of the present study are to test the suitability of a general sinusoidal function, derived using ordinary least squares and linear regression on the solitary independent variable *hour of day*; and visualize these daily patterns to identify peak occurrences across major categories of health and across major distinguishable time periods. The methods are straightforward and provide replicable and accessible tools for researchers and practitioners.

Materials and Methods

Data Source and Heritage

We analyzed the public research data-set for 13 consecutive years, 2010 to 2022, obtained from the NEMSIS project (NEMSIS, 2022d). The project is a collaboration between the U.S. National Highway Traffic Safety Administration's Office of EMS and the University of Utah's Technical Assistance Center. The center maintains and publishes a data standard modeled on and extending the patient care report, which is broadly used by agencies to document EMS events (American Academy of Orthopaedic Surgeons, 2021).

On an ongoing basis–beginning in 2006 with data from three states and growing to a national effort over sixteen years–NEMSIS has received, stored, and shared standardized EMS data from U.S. states and territories that in turn receive and curate event data from their individual EMS agencies. The overarching goal is to host research data to support various analyses–including evaluation of clinical interventions, performance benchmarks, and efficiency–for the improvement of pre-hospital patient care.

As recently as 2014, the NEMSIS version two data-set represented input from 45 states and approximately 72% of all EMS calls in the U.S. (Wei et al., 2019). A dip in state data submissions was observed after an update to the latest data standard in 2017; this was followed by alignments and adoption of the latest data standard. As of 2020, 47 states and three territories used the latest NEMSIS data standard to provide event data for nearly 43.5 million EMS activations (NEMSIS, 2022a). By 2021, research reported in almost 1,000 scholarly articles used the data-set (NEMSIS, 2022d). As of 2022, 54 U.S. states and territories contribute their data to the project (NEMSIS, 2023).

Data Description and Provenance

The NEMSIS data-set, although it is a substantial collection of nearly complete EMS event activity, is an acknowledged convenience sample. Captured event data includes information from emergency management system software, such as time-stamps for the receipt of the EMS call and agency assignment. It also includes monitored patient vitals such as pulse rate, oxygen level, blood pressure, outputs from various electronic devices e.g., pulse oximeter, automated blood pressure cuff, 12-lead heart monitor, and manual entry of event information such as a statement of the patient's chief complaint recorded by paramedics or emergency medical technicians. As pre-hospital healthcare providers, paramedics and emergency medical technicians are responsible for completing a patient care report at the conclusion of each patient encounter, which begins with the EMS agency's response, triggered by an EMS call (American Academy of Orthopaedic Surgeons, 2021). The workflow involved in a patient encounter starts with a system-generated date and time-stamp that records when the call was received and when the EMS agency was dispatched. At public-safety answering points, trained call-operators who are certified emergency medical dispatchers code the reason for the call; see Table 4.[1] Such reasons are part of the universal standard known as the Medical Priority Dispatch System (International Academics of Emergency Dispatch, 2022), and have a near one-to-one mapping to recorded dispatch types (NEMSIS, 2022b,c).

Established in 1979, the Medical Priority Dispatch System provides 33 protocols that correspond to the chief complaints reported by callers, including emergency life events related to medical conditions such as stroke, chest pain, heart problem, diabetes,

[1]Other reasons include automated crash notification, fire, medical alarm, healthcare professional/admission, pandemic/epidemic/outbreak, standby, well person check, air medical transport, intercept, altered mental status, and no other appropriate choice.

convulsions/seizures, fainting, sick person, and breathing problems, as well as injuries triggered by a physical incident such as an assault, stabbing, gunshot, motor vehicle accident, fall, drowning, or electrocution, or a lightning strike, drug overdose, poisoning/ingestion, imminent (baby) delivery, and more. Emergency medical dispatchers not only facilitate the initial data-gathering but are responsible for determining the reason category which best matches the chief complaint described by the caller and for providing pre-arrival instructions such as cardiopulmonary resuscitation steps and the administration of epinephrine, naloxone, or aspirin.

Data from patient care reports, completed by local EMS agencies, is sent to the state where it is compiled and submitted to the national public research database. This database contains all patient events provided by states in a fully de-identified form that is absent the patient's name and address, the provider agency, the transport destination facility, and all geographic information except the U.S. census region/division and an urban/rural indicator, so that event data is compliant with the Health Insurance Portability and Accountability Act of 1996 as well as state data agreements. While some variations in state participation and submitted data do exist (NEMSIS, 2022a), date and time-stamps for EMS calls are pristine, likely because they are predominantly captured by automated public-safety management systems. Figure 1 shows the time-stamped sub-events available within the timeline of a single patient care event.

Preparation of the Data for Modeling and Analysis

This subsection describes the process used in this study to organize the NEMSIS event data in preparation for various pattern exploration activities, including visualization, mathematical transformation, model fitting, and statistical analysis. Our study used data from thirteen consecutive annual releases of the public research data-set, from years 2010 to 2022, totaling 311,848,450 EMS activations. A first step in the analysis involved harmonizing codes in the established protocol standards of dispatch (International Academics of Emergency Dispatch, 2022) with NEMSIS version two and version three standards (NEMSIS, 2022b,c). The aligned data is summarized under the 33 categories in Table 4, columns 1 and 2. For example, for the overdose/poisoning/ingestion category, 5,782,437 activations were submitted to NEMSIS over the thirteen year period.

The next step in the data preparation process was, for each category, to bin each activation based on the hour of day an EMS unit was assigned by dispatch. We used the data element for unit dispatch date/time, known by its element name as eTimes.03 in version three (NEMSIS, 2022c) and as E05_04 in version two (NEMSIS, 2022b). The time-stamp corresponding to unit dispatch was used in this analysis because onset times are often rough estimates or are not available. It is noteworthy that public-safety call processing times are generally short. Still, call processing plus caller hesitancy (i.e., call-in delays following an incident or onset) could potentially bias the horizontal shift.

Since time-stamps are recorded based on the public-safety call center location, time zone was automatically accounted for, although we note the possibility of bias within time zones. For example, Montgomery, Alabama lies approximately 1,000 due east of Van Horn, Texas – both are in the U.S. central time zone, have approximately the same hours of daylight each day, but have sunrise (and sunset) times that are more than one hour different. That is, by the time the sun rise occurs in Van Horn, people in Montgomery will have already experienced over an hour of daylight, even though the clock time in both places is identical. Variation such as this, within time zones, can explain variance in peaks and nadirs in processes that are governed by exposure to daylight.

The binning process converted the 311,848,450 activations to 113,952 bins for each of the 33 categories–that is, one bin for each hour in the period from midnight on January 1, 2010, to midnight on December 31, 2022, or 4,748 days times 24 hours. The set of 113,952 binned observations, corresponding to hourly dispatches for a given category over the thirteen years, is called a horizon data-set for this analysis. A final step in the preparation process was to summarize each category by a set of 24 hourly occurrence frequency bins, which is called a 24-hour compressed data-set.

Modeling and Analysis Methodology

Once the data was prepared into hourly bins, the analysis proceeded by first using visualization to examine the daily pattern shapes for each medical emergency dispatch type via hourly histograms, also known as discrete empirical distributions. From the visualizations, we recognized a strong presence of a sinusoidal function, with a single peak and nadir during a 24 hour period, across all categories. This pattern was formalized by using sinusoidal regression to fit a model for each category, which allowed us to statistically test parameter significance, to assess overall goodness-of-fit, and to observe the degree to which variance was described by each model. An appendix of this paper describes detailed steps for transforming data that graphically exhibits a nonlinear sinusoidal form. The transformation allows for the direct use of standard linear regression techniques.

To compare models across categories, we graphed peak and nadir times along with 95% confidence and prediction limits. Determining the peak and nadir point estimates used a small amount of calculus: We set the first derivative of each fitted sinusoidal function to zero and solved to find the maximum and minimum points, respectively. Confidence and prediction limits for these points were computed next. Various methods for estimating calibration limits from a regression model are available (Lin and Liu, 2005; Ng and Pooi, 2008); we chose to use a method known as "Single-Use Calibration Intervals" for its simplicity (National Institute of Standards and Technology, 2012, Section 4.5.2.1).

To assess variation from a normative (or reference) pattern, i.e. a nearly common shape across all medical emergency dispatch categories, we computed the empirical cumulative distribution function *CDF* for each type. The *CDF* for each category was visualized alongside a reference pattern constructed from observations outside the targeted category. Pairwise statistical comparisons were performed via two-sample Kolmogorov–Smirnov (Massey, 1951; Boo et al., 2018) and Cramér-von Mises (Anderson, 1962) tests, as well as Chi-Square (Moore, 1986; Ross, 2014) tests and the Wasserstein metric which is also known as the *Earth Mover's distance* (Duda, 2018).

After analyzing the daily pattern by the 33 medical emergency dispatch types, we followed the same methodologies to examine daily patterns for the data-set reorganized into monthly, seasonal, daylight-savings/civil time, and pre-/post-COVID-19 periods. Motivated by the fact that the 33 medical emergency types follow from chief complaint and priority symptoms observed by dispatch, and thus do not represent final diagnoses, we investigated the pattern of a medical emergency that is uniquely diagnosed in the field: acute myocardial infarction (*heart attack*). The next sections provide the results of analyses as well as discussion and conclusions.

Results

Our study analyzes hourly occurrence patterns from 311,848,450 events over a thirteen year period, sourced from NEMSIS; see Table 3. Our analyses show that a sinusoidal equation fits all emergency dispatch categories, establishing the notion of a common, predictable daily pattern of rhythms at the population level. We found that daily EMS patterns for acute myocardial infarction (heart attack), chest pain, heart problems, stroke, convulsions and seizures, and sudden cardiac arrest/death exhibit peak occurrences in the early to mid afternoon, in contrast to previously found morning tendencies. Our analysis of the daily pattern for heart attack are based on field diagnoses by 12-lead cardiac monitor.

The number of total activations used in model building ranged from just over 72,000 (electrocutions and lightning strikes) to more than 52 million (general sick person), per category, for the thirteen years covered by the NEMSIS data-set. With the exception of two previous studies, one of comparable size which was really a meta-analysis of 30 studies (Cohen et al., 1997) and one which is roughly twice the size of our smallest (Tripathi et al., 2020), the patient event numbers used to model the daily patterns in our investigation dwarf sizes of studies cited in Tables 1 and 2. In the data, there were more than half a million activations for almost 85% of the medical event categories; three quarters had more than one million activations; and nearly 30% had more than 10 million activations; see Table 4.

Sub-Figures 2a through 2ag show the visualizations of the daily patterns, based on hourly call frequencies, for each medical emergency category described in Table 4, together with the fitted parameters for the sinusoidal equation. Table 5 provides the results of the 33 sinusoidal regressions, one row per medical emergency category. Regression parameter estimation, together with the visualizations, confirmed the strong daily sinusoidal form, with 24-hour cycles, peaks, and nadirs across all types. All 33 models have statistically significant coefficient estimates at the $\alpha = 0.05$ level: In 28 of the 33 medical emergency categories, model fitting yielded coefficient estimates with p-values of less than 0.01%. For three of the remaining five models, carbon monoxide/hazmat/inhalation/CBRN, choking, and pregnancy/childbirth/miscarriage emergencies, only the $\hat{\beta}_1$ coefficient estimates were "less" significant–i.e., $p < 0.1\%$ for one and $p < 1\%$ for the other two. Inspection of visualizations in Figure 1 shows all three models with subtle evidence of a bimodal distribution.

The coefficient of determination, R^2, varied from 84.20% (82.70% adjusted R^2; pregnancy emergencies) to 98.85% (98.74% adjusted R^2; industrial accident medical emergencies) with most in the mid to high 90%'s, indicating that all sinusoidal models explain hourly variation quite well. (See Table 5.) All 33 models resulted in diminutive root mean square error (RMSE) values ranging from 0.0018 to 0.0083. The tiny RMSE values are further indication, based on the combined magnitude of residuals, of the models' aptness in fitting the data-sets. (See Table 5, far right column.)

The timelines shown in Figure 3 illustrate the peak and nadir for each of the 33 daily medical emergency time-of-day patterns, along with corresponding confidence and prediction interval estimates. This figure underscores the consistency of the daily patterns of medical emergencies and shows that all but three have confidence and prediction intervals that span the afternoon. The visualization and sinusoidal regression results indicate a common, normative daily pattern across medical emergency dispatch categories. Visualizations comparing the empirical CDF for each medical event category to a normative distribution formed by all other event data are given in Figure 4, with statistical comparisons in Table 6. While there are subtle deviations in the pairwise visual comparisons of some CDFs, the statistical comparisons show no significant differences.

After analyzing major medical dispatch categories, which showed a consistent afternoon peak across types, we extended the analysis to assess whether a daily normative pattern persists by considering monthly, seasonal, daylight-savings/civil time, and pre-/post- COVID-19 period effects. Results of analysis seeking evidence of these potential factors contributing to other hourly variance are summarized in the peak and nadir timelines of Figure 5. None of these factors showed an influence on the daily patterns. A daily pattern specific to heart attacks (diagnosed by EMS responders in the field) was also found to be consistent with the normative pattern, peaking in mid-afternoon. These results are discussed in more depth in the next section.

Discussion

In this study, we aimed to explore time-of-day patterns from the voluminous and rich NEMSIS data-set. The statistical significance of all models and their visually prominent shapes corroborate the idea of a normative daily pattern for emergency medical events. The daily temporal patterns that emerged are distinct and remarkable, suggesting that they are normative. While the data and analysis represent an observational study, that the found daily patterns are formed from voluminous data-set, drawn nationally and over a thirteen year period, gives credence to the results of this paper. While all 33 event types follow this same pattern, there is variability with respect to time of day for peaks and nadirs by medical event type. The daily pattern analysis shows that, for 30 of the 33 emergency medical events, EMS calls peak during early to mid afternoon. The remaining three medical emergencies peak in the early evening hours.

Our study – based on 13 years of systematically curated U.S. national data comprised of nearly one third billion events – reveals that a common pattern persists across the 33 standardized dispatch categories, various time periods, and field diagnosed heart attacks. However there are distinct differences in peak time of occurrence and within the distribution of several of these categories. Four daily patterns, while showing exceptional fit to the sinusoidal function (Table 5), show visual evidence of a bimodal distribution. These patterns correspond to the following four major categories; a.) carbon monoxide/hazmat/inhalation/CBRN (NEMSIS version three, dispatch type 2301017); b.) choking (NEMSIS version three, dispatch type 2301023), c.) pregnancy/childbirth/miscarriage (NEMSIS version three, dispatch type 2301057), and d.) traffic/transportation incident (NEMSIS version three, dispatch type 2301069). Their patterns correspond to sub-Figures 2h, 2k, 2x, and 2ac respectively and each is, arguably, a combination of individual daily patterns. For example, choking (Sub-Figure 2k) appears to have lunch- and dinner-time sub-patterns, while morning and evening bursts of CBRN (predominantly carbon monoxide exposures) suggest there may be reason-driven sub-patterns (sub-Figure 2l).

Pregnancy emergencies (sub-Figure 2x) also appear to follow a subtle bi-modal shape. Recall that coefficient estimates $\hat{\beta}_1$, $\hat{\beta}_2$, and $\hat{\beta}_3$ correspond to the vertical displacement, horizontal shift, and amplitude, respectively. Since horizontal shift determines peak and nadir times of day, it is logical that bi-modal patterns–insinuated by visual inspection–lead to "less significance" for the $\hat{\beta}_1$ estimate. This is true for the first three of these four patterns, i.e. their sinusoidal model parameter estimates are all significant, but some with higher p values. The fourth is the pattern for injuries related to traffic and transport incidents shown in sub-Figure 2ac which shows swells occurring during common morning and evening commute times as well as model parameters all at $p < 0.1\%$ levels.

Three "exception" patterns peaking after 6 PM, as opposed to the more common mid-afternoon timing, are: a.) assault (NEMSIS version three, dispatch type 2301007); b.)

overdose/poisoning/ingestion (NEMSIS version three, dispatch type 2301053), which includes alcohol and other drugs as well as poisonings and ingestions; and c.) stabbing/gunshot wound/penetration traumas (NEMSIS version three, dispatch type 2301063). Their patterns correspond to sub-Figures 2d, 2w, and 2aa respectively. These categories are distinguished from other medical emergencies because assaults, stabbings/gunshot wound and penetration trauma are forms of interpersonal violence. The overdose/poisoning/ingestion anomaly needs further analyses and is reflective of the opioid addiction and overdose epidemic that has plagued the U.S. for decades. Potential explanations for the later tendency for this group include non-biomedical factors that could influence the timing of events leading up to one of these injuries and overdoses, and subsequent call for medical help. The evening peak timing is after normal work and school hours. In these cases, the distress calls appear to follow human activity and behaviors post work and school hours.

The consistency of the daily pattern across medical emergencies, which run the gamut in terms of potential threats to life, seem to indicate that the human sleep/wake pattern is the predominant factor in time-of-day occurrence tendency. This indication is re-enforced from the comparative analysis on empirical CDFs, as well as the period- and heart attack-specific daily patterns. The common patterns shown in our results warrant further investigation via more targeted studies that examine the causes, risks, and protections by emergency medical event type as well as correlations across categories. Such investigations may help to uncover whether or not the time-of-day patterns found in this research, which are consistent across seemingly unlike medical emergencies, might be explained by the mere propensity for human events to occur squarely in the middle of a wake-state cycle. That the general pattern is shared, even between seemingly non-similar medical emergencies, suggests a need for studies to unravel what people are doing immediately beforehand.

We note that dispatch types such as chest pain, heart problem, convulsion/seizures, and psychiatric problem/abnormal behavior/suicide attempt are not one-to-one with the categories used in previous studies: heart attack, congestive heart failure, epileptic seizure, and suicide attempts or ideation; see Tables 1 and 2. For one, a category represents the patient's chief complaint, noted at the time of call receipt, whereas most previous studies are based on medical diagnoses by physicians. Nevertheless, the categories intersect, even with error in the upstream process. For example, a medical emergency with the chief complaint “breathing problem” is a potential heart attack when accompanied by chest pain, nausea, sweating, irregular heart beat, and weakness–symptoms that might not be mentioned in the call conversation. In fact, a dispatch for chest pain could end up being for a patient with a digestive system problem, such as severe heartburn.

In general, formal diagnoses are not made until a patient is seen by a physician in an emergency room, hospital, or clinical office. Even those diagnoses can be tentative until a patient follows up with specialists, has more diagnostic tests, or even (in case of expiring) is autopsied (Brush et al., 2017). One exception to this is that paramedics, in the field, can pronounce an acute myocardial infarction (heart attack) using a 12-lead electrocardiogram, also known as a heart or cardiac monitor. Since not all chest pain dispatches indicate a heart attack, we took advantage of the fact that the NEMSIS data-set can include an acute myocardial infarction impression (International Classification of Diseases version 10 code ***I21***, Centers for Medicare & Medicaid Services (2023)) and a corresponding data field interpreted from a field electrocardiogram reading. We used these data fields to isolate and observe the daily pattern for responses to acute myocardial infarction events to see if their pattern deviated from the chest pain pattern. Our analysis showed that in 694,505 distinguishable acute myocardial infarction events, the daily pattern was again close to the normative pattern, and similar to the pattern for chest pain dispatches, peaking in occurrence just before 3 PM. (See last line of Figure 5.) Our findings based on nearly 700,000 field-diagnosed heart attacks contrast significantly with studies that showed morning peaks for heart attack occurrences (Cohen et al., 1997; Muller et al., 1985). The mid-afternoon peak found in our study, and its similarity with patterns for other seemingly non-similar medical events, suggests that non-biomedical factors may be more consequential. Our study's results suggest that re-investigation is worth-while, particularly since pharmacological prevention of acute myocardial infarction is based heavily on predominant occurrence time-of-day assumptions (Ruben et al., 2019).

An emergency medical call to dispatch for medical assistance, along with its time-stamp, can be thought of as a distress signal that happens *during* a perceived medical emergency. That is, a medical emergency is arguably a continuous process that begins with symptom onset, and the call for help is merely a discrete point in time within process. Sometimes there is very little delay between the onset and the call, for example for a traumatic injury following a motor vehicle crash. In other times, there is hesitancy – for example, in the case of illegal drug overdose or other reasons for anxiety about being exposed to law enforcement (Wagner et al., 2019; Zoorob, 2020). For some medical conditions, a patient may not recognize their symptoms, or may be in denial, which has been documented for stroke (Fussman et al., 2010). In some cases, for example heart attack, certain symptoms may appear for hours in advance (Dracup et al., 1995; Finnegan et al., 2000). Currently, there seems to be only high level understanding of the circumstances leading up to decisions to call for EMS assistance. That is, it would be helpful in analyzing and interpreting daily patterns to know who, why, and when people decide to dial 9-1-1 – for example, in Canada, the U.S., Saudi Arabia, and others – or 1-1-2 – in Sweden, Turkey, and Portugal, and 9-9-9 in the United Kingdom (World Population Review, 2023). The vast majority of calls are made by a second party, i.e. a family member, friend, or bystander who is someone present with the patient and acting on their behalf (Clawson et al., 2015, Figures 3.5a, 3.5b). This is based on limited observation, but indicates that patients usually do not make a call for medical assistance themselves. How often and for how long might there be delays in calling between symptom onset and a distress call? This sort of behavior likely affects the variance and shift in daily patterns.

Daily pattern for EMS responses to convulsion/seizures (total 9,017,651; see Sub-Figure 2l) was also inconsistent with the patterns found by at least two previous studies. Activity for medical emergencies of this type peaked in the mid afternoon, at 3:28 PM, with a wide 95% confidence interval (just after noon to nearly 7 PM), see Figure 3. Two existing studies specific to epileptic seizures showed varying peaks under specific types of seizure, with a common tendency in the early morning hours (Pavlova et al., 2012; Ramgopal et al., 2012). The discord between the EMS pattern and these studies may be due to the fact that the convulsions/seizures dispatch type includes various causes, only one of which is epileptic seizure. The severity of the seizure, or the likelihood of its being witnessed, may also drive more calls during the day. This pattern needs much further investigation, including the etiology of convulsions and seizures and variations according to age group.

EMS responses to events in the category of falls (total, 27,130,646) is another example of a medical emergency that likely includes a large variation in reasons–from a workman falling off a roof to an older adult tripping on a rug. The daily pattern (sub-Figure 2q) and peak in mid-afternoon (Figure 3 in this case is consistent with previous findings that showed that posture control is better in the morning (Gribble et al., 2007). However, this category is likely composed of many causes, which could include biomedical factors as well. For example, drops in blood pressure or glucose can be fall causes.

Recognition of normative patterns across the spectrum of medical event types sets the stage for future research that could advance prevention sciences. There are clear patterns of peak occurrence for overdoses, work related injuries, recreational injuries, allergic reactions and general sickness, and cardiac events. As noted earlier, overdoses are more likely to occur in the early evening. These include opioid drug overdoses. Are overdoses more likely to peak in early evening hours because users work during normal business hours and therefore the opioids are taken after work? Or is there a relationship to a natural cycle or circadian rhythm of neurotransmitter release that affects vulnerabilities for overdose (Koob et al., 1998; Kosobud et al., 2007; Tomkins and Sellers, 2001)? Might the hourly occurrence patterns identified in the present study enhance the design of addiction treatment (Webb, 2017)? Similarly, given that emergencies such as burns/explosions, electrocution, eye injuries, lacerations, drowning, and animal bites have predictable daily occurrence tendencies and that accidents are a leading cause of death in the U.S. (CDC, 2023), would these patterns be useful for designing prevention strategies in work and recreational settings?

Of note in the daily patterns is the fact that seemingly dissimilar medical events all tend to occur right around 3 PM; for example, abdominal pain, headaches, allergic reactions, fainting, and general sick person. Are there any inferences we can draw from this common hour of day? Likewise, back pain and non-traumatic chest pain emergency medical events are most alike in their tendency to peak around the same time–just after 1:30 PM, for reasons not yet understood. Breathing and heart problems emergency event tendencies also peak at around 3 PM, with 95% confidence interval from 1 to 5 PM and 95% prediction interval from just before noon to just after 6 PM. Could this be due to a similar or shared causes?

In summary, our analysis revealed a robust daily pattern in the hourly distribution of occurrences across 33 major categories of medical emergencies. The consistent pattern persisted in extended analyses organized around periods (month, season, daylight-savings/civil time, COVID-19), and heart attack-specific events. The common sinusoidal cycle demonstrates that all categories of medical emergencies appear to be influenced by an underlying daily rhythm. In several cases, the found daily patterns described in this paper are not consistent with long-established morning peaks: specifically for acute myocardial infarction, chest pain, heart problems, stroke, convulsions and seizures, and sudden cardiac arrest/death. In conclusion, recognition of the trend in daily patterns of medical emergencies raises many important questions about causes and prevention efforts. The daily predictable EMS patterns presented here may provide impetus for further research that links daily variation with causal factors, risks, and protections.

Limitations

We note that the 311,848,450 total activations, while a substantial observational data-set, may be influenced by duplicate or cancelled calls, and by recognized omissions. For example, the New York State Department of Health reported that as of January 1, 2020, all of its agencies were using the latest NEMSIS standard for electronic capture of patient care information, improving the quality and completeness of the data (New York State Department of Health, 2021). However, electronic data capture included only approximately 90% of statewide activations, reflecting submissions from about half of all certified agencies in the state. The remaining data–roughly 10% of statewide activations–were documented manually via paper patient care reports, and are not included in NEMSIS contributions.

It is important to note that a category is based on the best-known information at the time of EMS activation. For example, an activation for a breathing problem, fall, unconscious person, or cardiac arrest might be due to an opioid overdose, falling under the overdose/poisoning/ingestion category. In other words, as with any recording of data based on human communications and judgement, both error and re-diagnosis are possible. Due to the voluminous size of the data-set–nearly a third of a billion activations over a thirteen year period–our analysis assumes that such mis- or re-classifications are not more significant than a random effect in data. A study to estimate the magnitude of this effect is suggested for future research.

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Human Subjects Review

This project was reviewed and approved by the Syracuse University Office of Research Integrity and Protection and determined to be exempt.

Declaration of Conflicting Interests

The authors declare that there are no conflicting interests.

Appendix

This appendix describes the step-by-step process used to analyze patterns from the NEMSIS data-set, binned by hour of day. The modeling involves a standard polynomial transformation from trigonometry, used similarly by previous researchers (Eubank and Speckman, 1990). This development is designed so that sinusoidal regression modeling is understandable to all, and can be reproduced on any sort of similarly binned data. The mathematical elaboration of this section also reveals the equivalency to the cosine form which is popular for modeling biological rhythms. This approach for handling binned event data, from EMS or other processes, can be readily implemented using common statistical packages such as SAS, SPSS, STATA, R, Python, or an MS EXCEL spreadsheet.

Visualization and Sinusoidal Modeling

Plotting the 24-hour distribution for each dispatch category or period was the first step in the exploration phase of this research. The next methodological step was fitting the sinusoidal form (Freegarde, 2013; Vizireanu and Halunga, 2012) to the data for each category or period. We first characterized the sinusoidal form generally as:

$$Y = \mu + \rho \sin(\omega X + \theta) \tag{1}$$

which is a special case of the single-component cosinor (Cornelissen, 2014). Equation 1 computes Y, the probability of an EMS activation (of a specific category) occurring during hour X (the hour of the day – $0, \ldots, 23$). Parameters μ, ρ, ω, and θ fully characterize everything needed for the shape, location, and scale of the equation's form. Specifically:

$|\rho|$ reflects the sine wave's amplitude, or (in its absolute value) the high point of occurrences in the day; the amplitude is the hour corresponding to the highest percentage of dispatches;

ω is the frequency, computed from the observed period ($\omega = 2\pi/24$);

$\frac{2\pi}{\omega}$ is the period–the duration represented by a single sine wave (by ocular inspection, this is clearly 24 hours);

θ represents the horizontal shift of the sine wave, or the displacement of the wave's starting point to the right (or left, if negative) of the y axis;

$\frac{|\theta|}{\omega}$ is the horizontal shift scaled to the period; and

μ is the vertical shift–the displacement up (or down) from the x axis.

To derive parameters that could be estimated using ordinary statistical modeling, the following transformations were applied. First, the dependent variable was transformed by standardizing the time interval from $[0, 23]$ (hours) to radians:

$$\tilde{X} = 2\pi X/24 \tag{2}$$

The transformation of Equation 2 yields a period of 2π, with frequency ω equal to one–consistent with the visually verified shapes in Sub-Figures 2a through 2ag. A substitution from Equation 2 into Equation 1, with $\omega = 1$, results in:

$$Y = \mu + \rho \sin(\tilde{X} + \theta) \tag{3}$$

Using a basic trigonometry identity known as the angle-sum relation for the sine function (Zwillinger, 2018, p. 429), Equation 3 is equivalent to:

$$Y = \mu + \sin(\theta)\cos(\tilde{X}) + \rho\cos(\theta)\sin(\tilde{X}) \tag{4}$$

A diligent substitution of:

$$\left.\begin{array}{lll} \beta_0 & \text{for} & \mu, \\ \beta_1 & \text{for} & \sin(\theta), \\ \beta_2 & \text{for} & \rho\cos(\theta), \\ X_1 & \text{for} & \cos(\tilde{X}),\ \text{and} \\ X_2 & \text{for} & \sin(\tilde{X}) \end{array}\right\} \tag{5}$$

yields an equivalent equation:

$$Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 \tag{6}$$

Equation 6 is the widely known linear regression model. It comprises an intercept β_0 and a linear combination (in β_1 and β_2) of the dependent variables X_1 and X_2, which are transformations of the original dependent variable X in Equation 1. Parameters β_0, β_1, and β_2 are functions of the location and shape variables from Equation 1.

Equation 4 is not unfamiliar in health and statistical modeling. Public health researchers have long used it to model weekly and seasonal patterns of infectious disease outbreaks such as influenza. It resembles a form used by epidemiologists to model weekly or seasonal effects–for example, the Fourier terms in the negative binomial model (Noufaily et al., 2013, Section 3.1). It is also a variant of the cosine circadian and diurnal models (Germanó et al., 1984; Rodriguez-Zas et al., 2012; Ware and Bowden, 1977), and of basic signal processing used in engineering (Gold and Rader, 1969; Whalen, 1971).

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Table 1: A summary and analysis of recent articles that reported on time-of-day tendencies on medical events or illness onset. Recent studies have examined an array of event types, under various assumptions. However, most of the studies are small in terms of observational data size. Part 1 of 2.

Article and Studied Event or Onset	**Data Size, Period, Location**	**Daily Pattern Finding**	**Suggested Causes or Risks**	**Suggested Prevention**
Akkaya-Kalayci et al. (2017) Congestive heart failure	26,224 patients, 1988-1998, Northern NJ, USA	AM peak; rate increase starting after wake up	Catecholamine release	Beta blockers
Allegra et al. (2001) Suicide attempt	2,232 patients in 2010, Istanbul, Turkey	Evening peak	School stress; lack of structure; family event triggers	Hotlines and health services in evening hours
Buurma et al. (2019) Cardiovascular disease	Varies by cited study	Citing previous studies, AM changes in cardiovascular processes with negative impact on CVD	AM platelet activity	Aspirin chronotherapy
Cohen et al. (1997) Acute myocardial infarction (AMI); Sudden cardiac death (SCD)	64,589 across 30 studies, ranging from 148 to 12,161 events or patients; period/location vary by study	6AM to noon peak for both	Speculated; e.g. disruption of vulnerable atherosclerotic plaque followed by intra-coronary thrombosis	Long acting medications for AMI; dosing schedules
Dutta et al. (2021) Suicide ideation, atempts (social media posts)	1,494,897 social media posts; late 2008-mid 2016; virtual	Peak 2-5AM with nadir 11AM-2PM; Certain posters showed 8-11PM peak, coinciding w/ general posting peak	Mental health issues; attention seeking behavior	Appropriately timed prevention and counseling services
Elliott (1998) Stroke	11,816 events; 1871-1997; location varies by cited study	6AM to noon peak	Circadian patterns similar AMI and SCD causes	Antihypertensive agents administered in AM
Faramand et al. (2019) Chest pain	2,065 EMS events; Mid 2013-mid 2015; Pittsburgh, PA, USA	Peaked at 1PM, nadir at 6AM. AMI peaked at 10 AM or 10 PM depending on EKG	Primarily AMI	Prehospital providers, clinicians and hospital systems operating hours
Ferrazzi et al. (2018) General medical emergencies	66,527 visits and 84,380 return visits; 2007-2016; N. Italy	Photoperiod of day more significant than actual clock time	Natural light effect	Consider effect on DST design and A&E resource scheduling
Gribble et al. (2007) Posture control	30 college age students; 2 days prior to 2007 paper; Univ lab, Toledo, OH, USA	Posture control is better AM than afternoon or evening	N/A	More research needed; implications for return to play (sports)
Jasso et al. (2007) General medical emergencies	Hourly, half hour, quarter hour binning over 670 days; Mid 2004-mid 2007; San Francisco, CA, USA	Peak call volume at 3PM	General recognizing of diurnal pattern	Predicting call volumes for planning and reacting
Kerry et al. (2013) Hypoglycemia	771 events; Sept, Oct 2013; Ipswich, UK	Majority of events occurred in 9PM-9AM	Insufficient carbohydrate intake	Changes in catering
Manfredini et al. (2002) General medical emergencies	20858 events; 1998; Ferrara, Italy	AM peak for cardiologic, respiratory, and neurologic disease. Afternoon peak for trauma, neoplastic diseases, and acute poisoning.	N/A	Emergency department resource planning to match high demand periods
McCarthy et al. (2006) General medical emergencies	A representative sample of activity from 400 US emergency departments; 1996, 2000, 2004; US national	Nadir at 5PM; peaks at 11AM and 6PM	N/A	Calls for more research, and need for more data, information systems

Table 2: A summary and analysis of recent articles that reported on time-of-day tendencies on medical events or illness onset. Recent studies have examined an array of event types, under various assumptions. However, most of the studies are small in terms of observational data size. Part 2 of 2.

Article and Studied Event or Onset	Data Size, Period, Location	Daily Pattern Finding	Suggested Causes or Risks	Suggested Prevention
Muller et al. (1985) Acute myocardial infarction (AMI);	703 cases; 1978-1983; US national	Primary peak at 9AM; secondary peak at 8PM.	Biologically controlled rhythmic causes	Beta blockers; more research
Muller (1999) Cardiovascular events	Varies by cited study	Clear AM peaks	Processes following AM upright posture, initiation of daily activities. Increased vascular tone; arterial pressure; and coagulability. AM increase in cortisol causing arterial sensitivity to catecholamines.	Select avoidance of physical emotional stressors; timed medication therapy
Ni et al. (2019) Sudden cardiac arrest (SCA)	1535 events; 2002-2014 2002-2014; norther US community with 1M residents	Found no morning (6AM to noon) peak; midnight to 6AM nadirs; failed to reproduce previous studies	Unknown	Further investigation
Ohshige (2004) Ambulance use	N/A; 1994-2001; Yokohama, Japan	Evening peak; early morning nadir	Frequency of use may be influenced by provider availability	Primary care availability in evenings
Pavlova et al. (2012) Seizures	831 reports; N/A; n/A	Frontal seizures peak in early AM; temporal lobe seizures peak in early evening	Various speculated causes	Dosing antiepileptic meds to time of day
Ramgopal et al. (2012) Epilegtic Seizures (GTC)	71 patients 223 seizures; 5 years N/A; N/A	Varied patterns by sleep and age: 12-3AM, 6-9AM, 9AM-noon peaks	Sleep/wake cycles	Chronotherapy
Rocco et al. (1987) Transient myocardial ischemia	32 patients with ambulatory EKG monitoring; N/A	Peak in episodes 6AM-noon	Surge of ischemic activity in AM after waking from sleep	Angina drug therapy targeting morning administration
Thakur et al. (1996) Sudden cardiac death (SCD)	2,250 events; N/A; Urban area, unspecified	Low occurrence rate 12-6AM; 2.4-fold increase from 6AM-Noon	Results suggest a common pathophysiologic mechanism	N/A
Tripathi et al. (2020) Cardiac arrest	154,038 patients; 2000-2004 693 US centers	In-hospital cardiac arrest occurs with nearly = frequency throughout the day	A myriad effects of medical therapies while hospitalized	Use to anticipate events outside of hospital
Vencloviene et al. (2017) Atrial fibrillation (AF)	5,361 calls; 2990-2011; Kaunas city, Lithuania	35% in first half of the day, 37% in afternoon, 28% late in the evening or at night	Weather and air pollution	EMS be more prepared by weather and environmental reports
Vile et al. (2012) Ambulance use	An avg of 1011 calls per day; 2005-2009; Wales, UK	Cyclic pattern observed in figures; however, analyzed by shifts not hours	N/A	Accurate predictions of call volumes to improve service
Willich et al. (1987) Sudden cardiac death (SCD)	5209 cases; Mid 1960s-mid 1980s; Framingham, MA, USA	Peak incidence 7-9 AM; decreased incidence from 9AM-1 PM	Not specified; acknowledged limitation	N/A

Table 3: List of the number of EMS activations captured in the NEMSIS Public Research data-set for years 2010-2022. Observational data used in this study drew from this data, specifically for 33 target categories corresponding to major medical events and priority symptoms, described in Table 4. The isolated target categories resulted in 311,848,450 EMS activations analyzed in this study.

Year	NEMSIS Data Version	Total Activations (NEMSIS)	Target Category Activations
2010	v2	9,776,094	7,971,521
2011	v2	14,371,941	11,752,181
2012	v2	19,831,189	15,814,542
2013	v2	23,897,211	19,390,627
2014	v2	25,835,729	21,286,429
2015	v2	30,206,450	24,864,430
2016	v2	29,919,652	24,553,240
2017	v3	7,907,829	6,912,094
2018	v3	22,532,890	19,780,139
2019	v3	34,203,087	30,305,643
2020	v3	43,488,767	38,481,719
2021	v3	48,982,990	43,434,387
2022	v3	53,179,492	47,301,498
Total (2010-2022)		364,133,321	311,848,450

Table 4: A list of the 33 targeted medical event dispatches within scope of this study, along with a description of the elements used to isolate them within NEMSIS public research data-set, 2010-2022. The target activations column provides the total number of instances for each dispatch category.

Reason (Description)	NEMSIS Version 3	NEMSIS Version 2	Target Activations (2010-2022)	Daily Pattern Figure
Abdominal Pain / Problems	2301001	400	9,261,255	Fig. 2a
Allergic Reaction / Stings	2301003	405	1,989,554	Fig. 2b
Animal Bite	2301005	410	510,180	Fig. 2c
Assault	2301007	415	4,834,719	Fig. 2d
Back Pain / Non-Traumatic	2301011	420	3,022,121	Fig. 2e
Breathing Problem	2301013	425	27,707,426	Fig. 2f
Burns / Explosion	2301015	430	690,226	Fig. 2g
Carbon Monoxide / Hazmat / Inhalation / CBRN†	2301017	435	335,582	Fig. 2h
Cardiac Arrest / Death	2301019	440	4,581,316	Fig. 2i
Chest Pain / Non-Traumatic	2301021	445	18,034,696	Fig. 2j
Choking	2301023	450	908,315	Fig. 2k
Convulsions / Seizure	2301025	455	9,017,651	Fig. 2l
Diabetic Problem	2301027	460	5,095,457	Fig. 2m
Drowning / Diving / SCUBA Accident	2301081	465	125,071	Fig. 2n
Electrocution / Lightning	2301029	470	72,284	Fig. 2o
Eye Problem / Injury	2301031	475	298,327	Fig. 2p
Falls	2301033	480	27,130,646	Fig. 2q
Headache	2301037	485	1,505,375	Fig. 2r
Heart Problems / AICD	2301041	490	3,616,305	Fig. 2s
Heat / Cold Exposure	2301043	495	503,108	Fig. 2t
Hemorrhage / Laceration	2301045	500	5,316,362	Fig. 2u
Industrial Accident / Inaccessible Incident / Other Entrapments	2301047	505	135,077	Fig. 2v
Overdose / Poisoning / Ingestion	2301053	510	5,782,437	Fig. 2w
Pregnancy / Childbirth / Miscarriage	2301057	515	1,801,287	Fig. 2x
Psychiatric Problem / Abnormal Behavior / Suicide Attempt	2301059	520	10,027,625	Fig. 2y
Sick Person	2301061	525	52,086,436	Fig. 2z
Stab / Gunshot Wound / Penetrating Trauma	2301063	530	1,286,719	Fig. 2aa
Stroke	2301067	535	5,880,156	Fig. 2ab
Traffic / Transportation Incident	2301069	540	23,250,395	Fig. 2ac
Traumatic Injury	2301073	545	8,482,885	Fig. 2ad
Unconscious / Fainting / Near-Fainting	2301077	550	14,439,981	Fig. 2ae
Unknown Problem / Person Down	2301079	555	14,969,690	Fig. 2af
Transfer / Interfacility / Palliative Care	2301071	560	49,149,786	Fig. 2ag
Total			311,848,450	

† Hazmat indicates a possible exposure to hazardous materials; CBRN indicates a possible chemical, biological, radiological, or nuclear exposure (American Academy of Orthopaedic Surgeons, 2021, Chapter 40).

Table 5: Summary of sinusoidal regression results for the 33 targeted NEMSIS dispatch types. All coefficients are statistically significant, most at the $p < 0.0001$ level. The coefficient of determination (R^2) was between 0.84 and 0.99 for all models, with most falling in the mid- to high-90s.

NEMSIS Type (v3)	$\hat{\beta}_0$	95% Confidence Interval for $\hat{\beta}_0$	$\hat{\beta}_1$	95% Confidence Interval for $\hat{\beta}_1$	$\hat{\beta}_2$	95% Confidence Interval for $\hat{\beta}_2$	R^2	Adj. R^2	RSME
2301001	0.0417***	[0.0406 , 0.0427]	-0.0072***	[-0.0087 , -0.0057]	-0.0077***	[-0.0092 , -0.0063]	0.9137	0.9055	0.0023
2301003	0.0417***	[0.0400 , 0.0433]	-0.0101***	[-0.0125 , -0.0078]	-0.0199***	[-0.0222 , -0.0176]	0.9501	0.9453	0.0036
2301005	0.0417***	[0.0402 , 0.0431]	-0.0104***	[-0.0125 , -0.0084]	-0.0259***	[-0.0279 , -0.0238]	0.9743	0.9718	0.0032
2301007	0.0417***	[0.0402 , 0.0431]	0.0117***	[0.0096 , 0.0138]	-0.0145***	[-0.0166 , -0.0124]	0.9426	0.9372	0.0032
2301011	0.0417***	[0.0400 , 0.0434]	-0.0138***	[-0.0162 , -0.0114]	-0.0047**	[-0.0071 , -0.0023]	0.8811	0.8698	0.0038
2301013	0.0417***	[0.0403 , 0.0430]	-0.0086***	[-0.0105 , -0.0067]	-0.0075***	[-0.0094 , -0.0056]	0.8815	0.8703	0.003
2301015	0.0417***	[0.0407 , 0.0427]	-0.0074***	[-0.0088 , -0.0060]	-0.0183***	[-0.0197 , -0.0169]	0.9760	0.9737	0.0022
2301017	0.0417***	[0.0398 , 0.0436]	-0.0059**	[-0.0085 , -0.0032]	-0.0142***	[-0.0169 , -0.0116]	0.8723	0.8601	0.0042
2301019	0.0417***	[0.0399 , 0.0434]	-0.0144***	[-0.0169 , -0.0120]	-0.0064***	[-0.0089 , -0.0039]	0.8949	0.8849	0.0038
2301021	0.0417***	[0.0402 , 0.0431]	-0.0088***	[-0.0109 , -0.0068]	-0.0104***	[-0.0124 , -0.0083]	0.9002	0.8907	0.0032
2301023	0.0417***	[0.0383 , 0.0451]	-0.0080*	[-0.0128 , -0.0032]	-0.0306***	[-0.0354 , -0.0258]	0.8994	0.8899	0.0075
2301025	0.0417***	[0.0403 , 0.0430]	-0.0129***	[-0.0147 , -0.0110]	-0.0141***	[-0.0160 , -0.0122]	0.9558	0.9516	0.0029
2301027	0.0417***	[0.0406 , 0.0427]	-0.0094***	[-0.0109 , -0.0079]	-0.0096***	[-0.0111 , -0.0081]	0.9458	0.9406	0.0023
2301081	0.0417***	[0.0390 , 0.0444]	-0.0151***	[-0.0189 , -0.0113]	-0.0352***	[-0.0390 , -0.0314]	0.9537	0.9493	0.006
2301029	0.0417***	[0.0399 , 0.0434]	-0.0129***	[-0.0153 , -0.0104]	-0.0186***	[-0.0211 , -0.0161]	0.9449	0.9396	0.0039
2301031	0.0417***	[0.0403 , 0.0430]	-0.008***	[-0.0100 , -0.0061]	-0.0136***	[-0.0155 , -0.0117]	0.9336	0.9272	0.003
2301033	0.0417***	[0.0405 , 0.0428]	-0.014***	[-0.0156 , -0.0124]	-0.0108***	[-0.0124 , -0.0091]	0.9600	0.9562	0.0025
2301037	0.0417***	[0.0404 , 0.0429]	-0.0071***	[-0.0088 , -0.0054]	-0.0125***	[-0.0142 , -0.0107]	0.9344	0.9281	0.0027
2301041	0.0417***	[0.0400 , 0.0433]	-0.0129***	[-0.0153 , -0.0105]	-0.012***	[-0.0143 , -0.0096]	0.9194	0.9118	0.0037
2301043	0.0417***	[0.0379 , 0.0454]	-0.0232***	[-0.0285 , -0.0179]	-0.0287***	[-0.0340 , -0.0234]	0.9090	0.9004	0.0083
2301045	0.0417***	[0.0403 , 0.0430]	-0.0066***	[-0.0085 , -0.0047]	-0.0105***	[-0.0124 , -0.0086]	0.9007	0.8913	0.0029
2301047	0.0417***	[0.0408 , 0.0425]	-0.0165***	[-0.0177 , -0.0154]	-0.0176***	[-0.0188 , -0.0164]	0.9885	0.9874	0.0018
2301053	0.0417***	[0.0403 , 0.0431]	0.0045**	[0.00250 , 0.0064]	-0.0188***	[-0.0208 , -0.0168]	0.9520	0.9474	0.0031
2301057	0.0417***	[0.0409 , 0.0425]	-0.0018*	[-0.0029 , -0.0006]	-0.0054***	[-0.0066 , -0.0043]	0.8420	0.8270	0.0018
2301059	0.0417***	[0.0405 , 0.0429]	-0.0056***	[-0.0073 , -0.0039]	-0.018***	[-0.0196 , -0.0163]	0.9623	0.9587	0.0026
2301061	0.0417***	[0.0402 , 0.0431]	-0.016***	[-0.0181 , -0.0139]	-0.0105***	[-0.0126 , -0.0084]	0.9451	0.9399	0.0033
2301063	0.0417***	[0.0400 , 0.0433]	0.0088***	[0.0064 , 0.0111]	-0.0146***	[-0.0169 , -0.0123]	0.9168	0.9089	0.0036
2301067	0.0417***	[0.0397 , 0.0437]	-0.0218***	[-0.0247 , -0.0190]	-0.0129***	[-0.0158 , -0.0101]	0.9433	0.9379	0.0044
2301069	0.0417***	[0.0395 , 0.0439]	-0.0151***	[-0.0182 , -0.0120]	-0.0209***	[-0.0240 , -0.0178]	0.9345	0.9282	0.0048
2301073	0.0417***	[0.0409 , 0.0425]	-0.0099***	[-0.0110 , -0.0087]	-0.0192***	[-0.0204 , -0.0181]	0.9869	0.9856	0.0018
2301077	0.0417***	[0.0399 , 0.0434]	-0.0167***	[-0.0192 , -0.0143]	-0.0146***	[-0.0171 , -0.0122]	0.9448	0.9395	0.0038
2301079	0.0417***	[0.0406 , 0.0428]	-0.0122***	[-0.0138 , -0.0107]	-0.0132***	[-0.0148 , -0.0117]	0.9658	0.9625	0.0024
2301071	0.0417***	[0.0395 , 0.0438]	-0.0248***	[-0.0279 , -0.0218]	-0.0129***	[-0.0160 , -0.0099]	0.9468	0.9418	0.0047

$^{*}p < 0{\cdot}01$ $^{**}p < 0{\cdot}001$ $^{***}p < 0{\cdot}0001$; $R^2 \equiv$ coefficient of determination; RMSE ≡ root mean squared error.

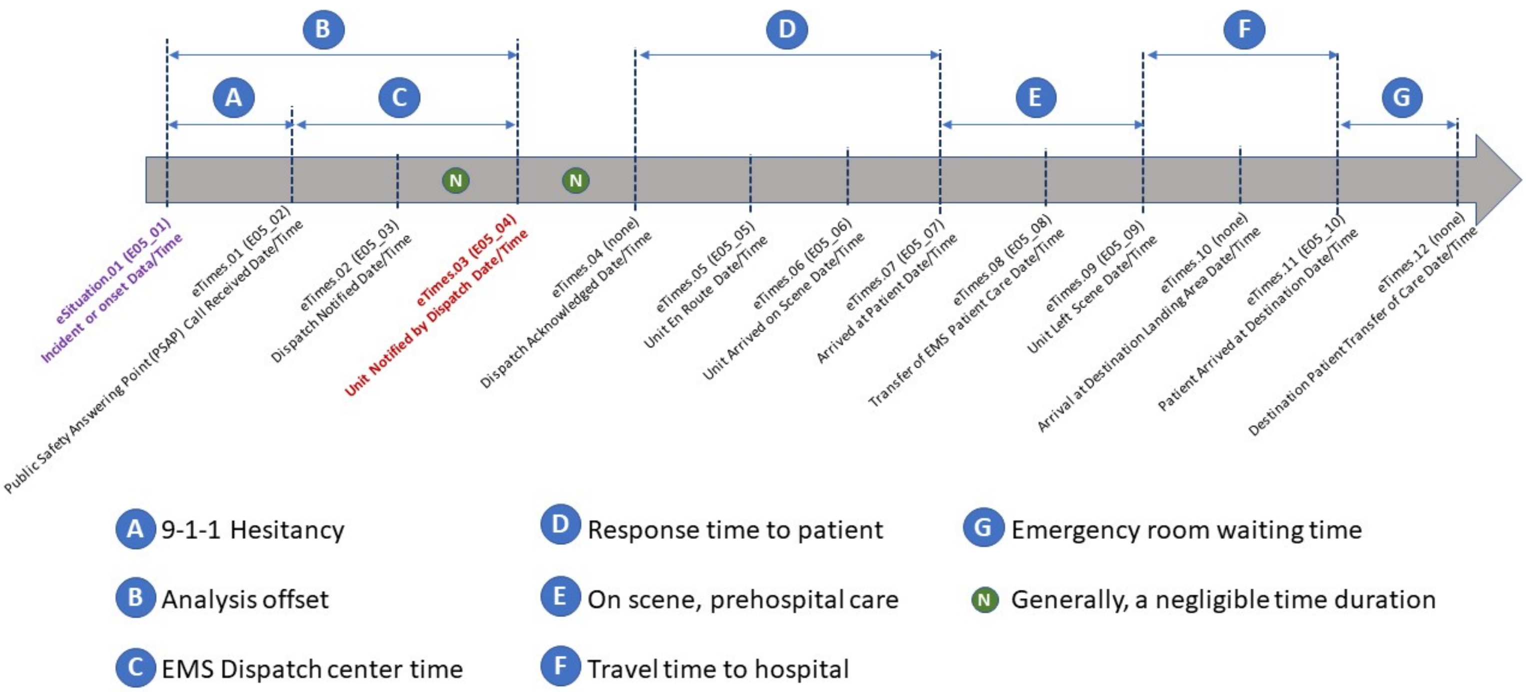
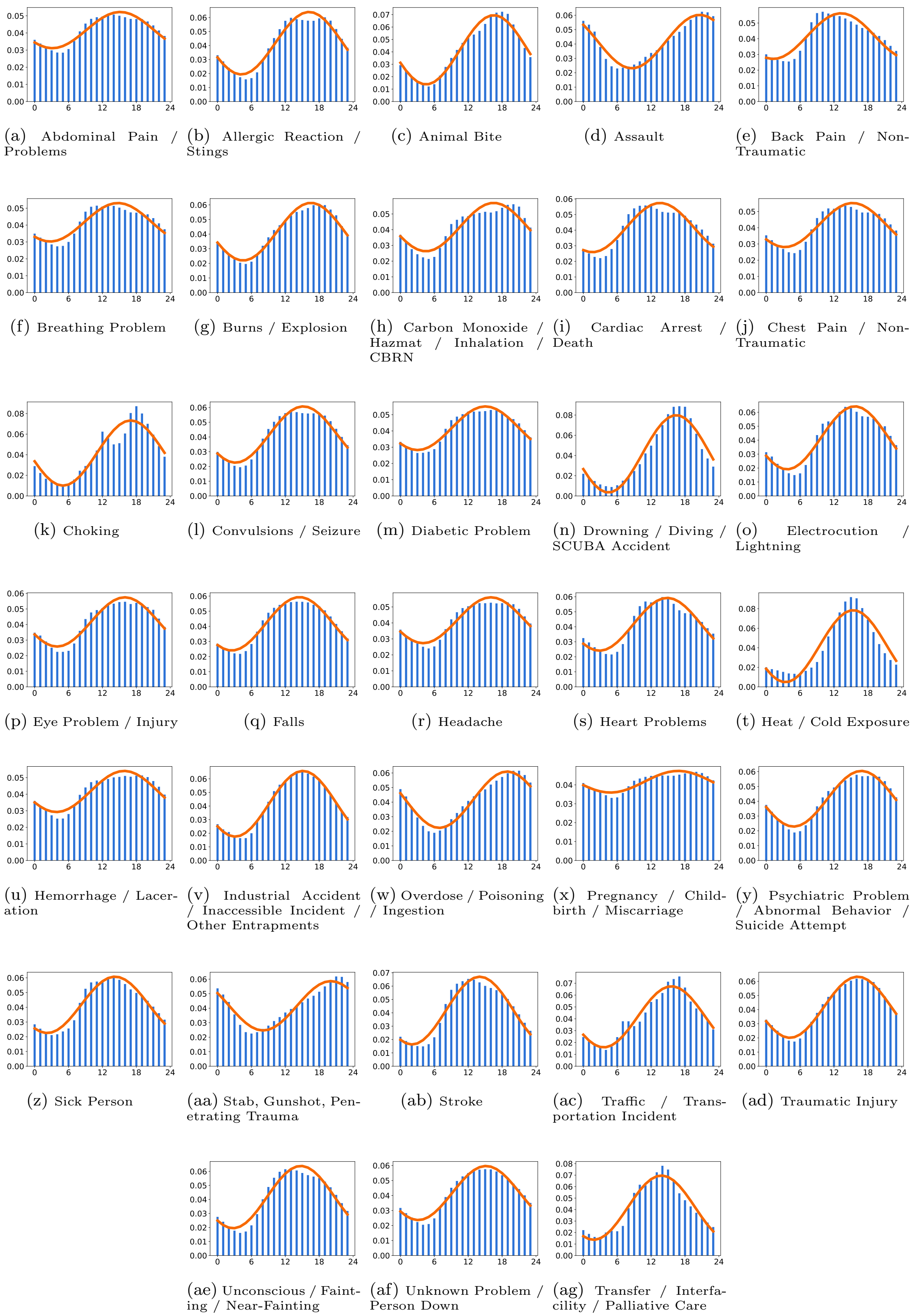


Figure 1: A timeline showing emergency medical services (EMS) events and activities during an activation in response to the emergency medical distress call for a single patient event. The data for time-stamps and element names is from NEMSIS, described in user documentation version 3 (NEMSIS, 2022b) and, in parentheses, version 2 (NEMSIS, 2022c). eTimes.03 (E04_04) in red is the time-stamped used as the event occurence reference point for this analysis. The interval defined by B illustrates the potential time delay between symptom onset and EMS dispatch time, which is elusive due to the subjective nature of reported symptoms prior to the distress call.



(a) Abdominal Pain / Problems
(b) Allergic Reaction / Stings
(c) Animal Bite
(d) Assault
(e) Back Pain / Non-Traumatic
(f) Breathing Problem
(g) Burns / Explosion
(h) Carbon Monoxide / Hazmat / Inhalation / CBRN
(i) Cardiac Arrest / Death
(j) Chest Pain / Non-Traumatic
(k) Choking
(l) Convulsions / Seizure
(m) Diabetic Problem
(n) Drowning / Diving / SCUBA Accident
(o) Electrocution / Lightning
(p) Eye Problem / Injury
(q) Falls
(r) Headache
(s) Heart Problems
(t) Heat / Cold Exposure
(u) Hemorrhage / Laceration
(v) Industrial Accident / Inaccessible Incident / Other Entrapments
(w) Overdose / Poisoning / Ingestion
(x) Pregnancy / Childbirth / Miscarriage
(y) Psychiatric Problem / Abnormal Behavior / Suicide Attempt
(z) Sick Person
(aa) Stab, Gunshot, Penetrating Trauma
(ab) Stroke
(ac) Traffic / Transportation Incident
(ad) Traumatic Injury
(ae) Unconscious / Fainting / Near-Fainting
(af) Unknown Problem / Person Down
(ag) Transfer / Interfacility / Palliative Care

Figure 2: Daily patterns for all 33 NEMSIS dispatch types, derived from sinusoidal regression. x-axis is the (military) hour of day. y-axis is the frequency (percent) of dispatch events in the hour. Blue bars are observations to form the 24-hour distribution, from 2010-2022 NEMSIS data. The red line is the fitted sinusoidal regression model. See equation 1 and its derivation in the Appendix.

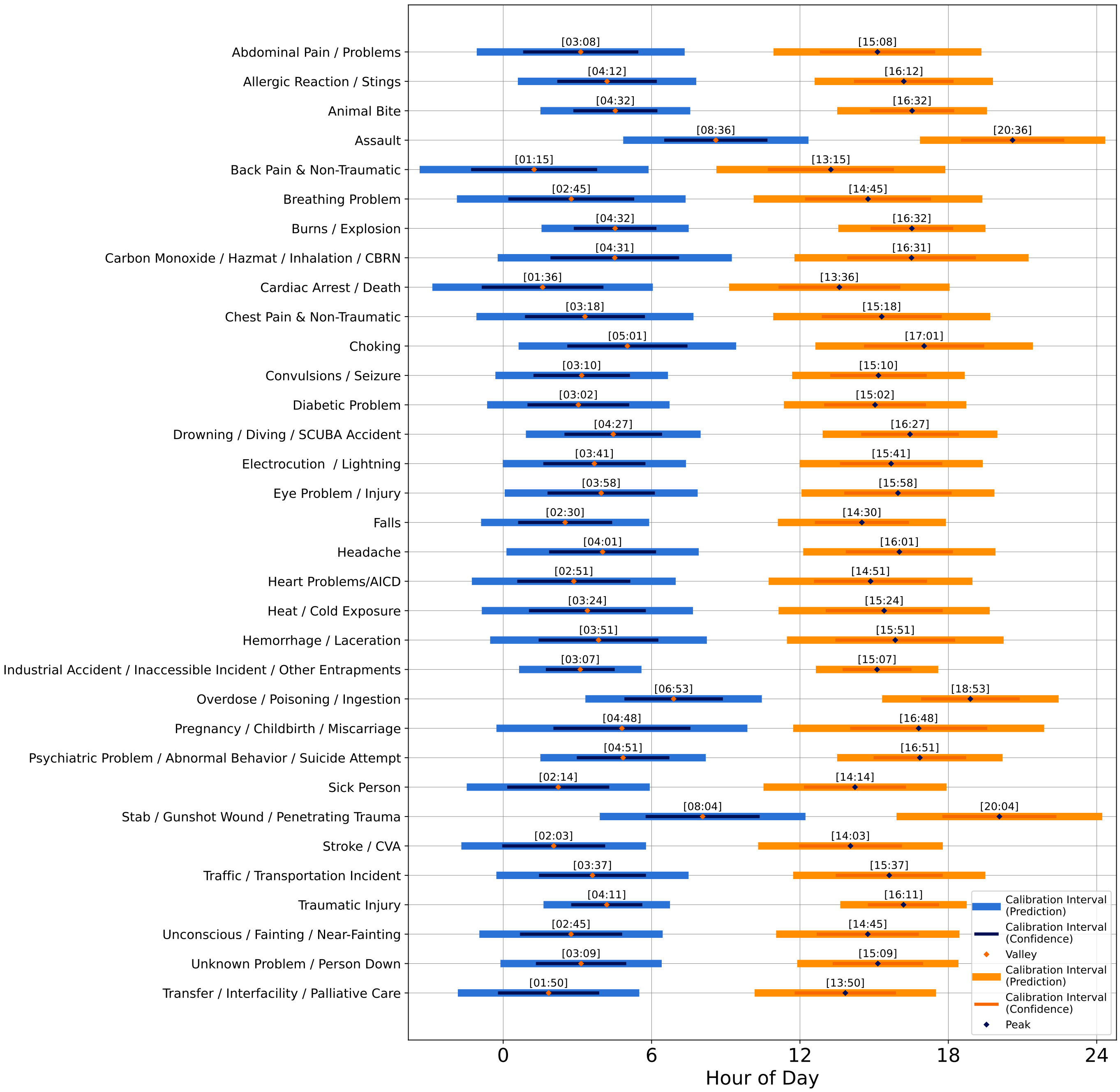
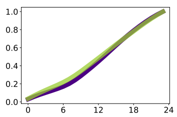
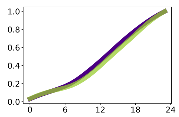


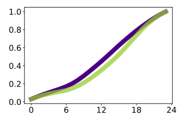
Figure 3: Peak and nadir times of day for each of the 33 targeted dispatch types, shown with calibrated intervals derived from the 95% prediction limits and 95% confidence intervals. The peak and nadir times are found via the first derivative of the fitted sinusoidal function for each type. Intervals are estimated using the standard error from the regression model.



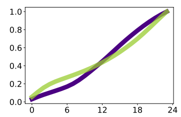
(a) Abdominal Pain / Problems



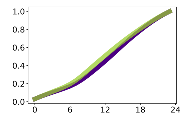
(b) Allergic Reaction / Stings



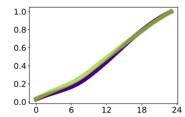
(c) Animal Bite



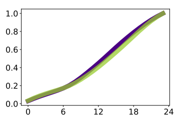
(d) Assault



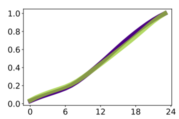
(e) Back Pain / Non-Traumatic



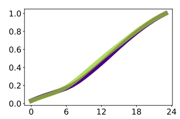
(f) Breathing Problem



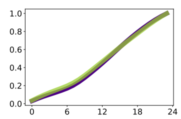
(g) Burns / Explosion



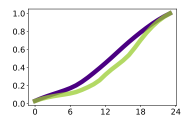
(h) Carbon Monoxide / Hazmat / Inhalation / CBRN



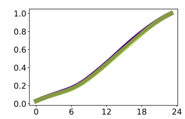
(i) Cardiac Arrest / Death



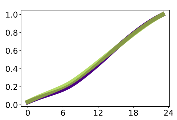
(j) Chest Pain / Non-Traumatic



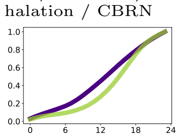
(k) Choking



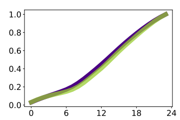
(l) Convulsions / Seizure



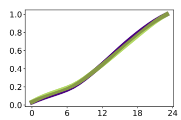
(m) Diabetic Problem



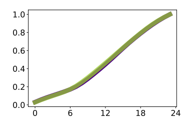
(n) Drowning / Diving / SCUBA Accident



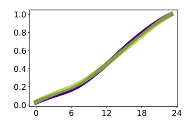
(o) Electrocution / Lightning



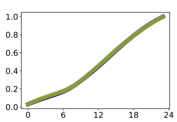
(p) Eye Problem / Injury



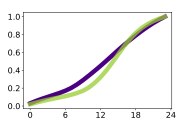
(q) Falls



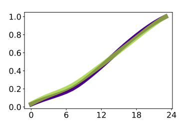
(r) Headache



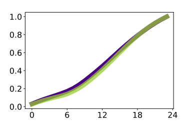
(s) Heart Problems / AICD



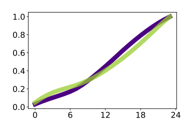
(t) Heat / Cold Exposure



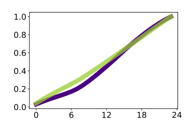
(u) Hemorrhage / Laceration



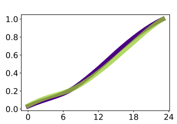
(v) Industrial Accident / Inaccessible Incident / Other Entrapments



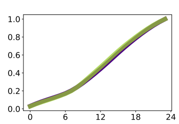
(w) Overdose, Poisoning



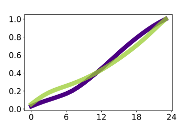
(x) Pregnancy / Childbirth / Miscarriage



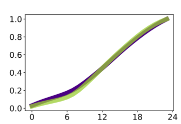
(y) Psychiatric / Abnormal Behavior / Suicide Attempt



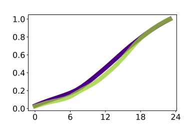
(z) Sick Person



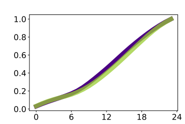
(aa) Stab / Gunshot Wound / Penetrating Trauma



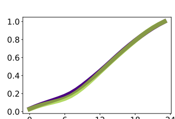
(ab) Stroke



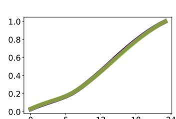
(ac) Traffic / Transportation Incident



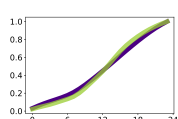
(ad) Traumatic Injury



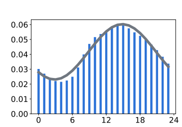
(ae) Unconscious / Fainting / Near-Fainting



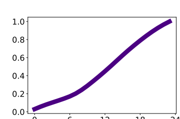
(af) Unknown Problem / Person Down



(ag) Transfer / Interfacility / Palliative Care



(ah) Reference Pattern



(ai) Reference Pattern

Figure 4: Visual comparison of each dispatch category's hourly empirical cumulative distribution (in green) with the empirical distribution from all other categories (in purple). Subfigures 4ah and 4ai are the overall histogram and cumulative distribution, i.e. the *reference pattern*.

Table 6: Summary of test statistics comparing the empirical cumulative distribution for each dispatch category to the empirical cumulative distribution formed by all other categories. The rows of the Table are ordered by ascending Wasserstein distance between the category's empirical c.d.f. and the normative pattern c.d.f. from all other observations. The Wasserstein distances, also called Earth Mover's distances, and the test statistics show that the c.d.f.'s are very close – and not significantly different from one another.

Rank[a]	NEMSIS V3 Code	NEMSIS Dispatch Reason (Description)	KS[b] stat	KS[b] p	CVM[c] stat	CVM[c] p	CS[d] stat	CS[d] p	Wasser-stein distance[e]
-	All	Reference Pattern	0.0000	1.0000	0.0000	1.0000	0.0000	1.0000	0.0000
1	2301079	Unknown Problem / Person Down	0.0417	1.0000	0.0100	1.0000	0.0011	1.0000	0.0042
2	2301041	Heart Problems/AICD	0.0417	1.0000	0.0100	1.0000	0.0024	1.0000	0.0050
3	2301033	Falls	0.0417	1.0000	0.0104	1.0000	0.0034	1.0000	0.0064
4	2301025	Convulsions / Seizure	0.0417	1.0000	0.0104	1.0000	0.0025	1.0000	0.0086
5	2301061	Sick Person	0.0417	1.0000	0.0100	1.0000	0.0046	1.0000	0.0098
6	2301077	Unconscious / Fainting / Near-Fainting	0.0833	1.0000	0.0139	1.0000	0.0083	1.0000	0.0121
7	2301031	Eye Problem / Injury	0.0417	1.0000	0.0100	1.0000	0.0107	1.0000	0.0137
8	2301027	Diabetic Problem	0.0833	1.0000	0.0122	1.0000	0.0100	1.0000	0.0150
9	2301037	Headache	0.0833	1.0000	0.0135	1.0000	0.0140	1.0000	0.0160
10	2301021	Chest Pain / Non-Traumatic	0.0833	1.0000	0.0152	1.0000	0.0112	1.0000	0.0161
11	2301019	Cardiac Arrest / Death	0.0417	1.0000	0.0100	1.0000	0.0186	1.0000	0.0186
12	2301017	Carbon Monoxide / Hazmat / Inhalation / CBRN	0.0417	1.0000	0.0100	1.0000	0.0212	1.0000	0.0193
13	2301047	Industrial Accident / Inaccessible Incident / Other Entrapments	0.0833	1.0000	0.0152	1.0000	0.0114	1.0000	0.0194
14	2301045	Hemorrhage / Laceration	0.0833	1.0000	0.0174	0.9999	0.0179	1.0000	0.0195
15	2301067	Stroke	0.1250	0.9942	0.0256	0.9965	0.0272	1.0000	0.0204
16	2301029	Electrocution / Lightning	0.0833	1.0000	0.0122	1.0000	0.0159	1.0000	0.0224
17	2301015	Burns / Explosion	0.0417	1.0000	0.0100	1.0000	0.0209	1.0000	0.0237
18	2301073	Traumatic Injury	0.0417	1.0000	0.0100	1.0000	0.0187	1.0000	0.0240
19	2301013	Breathing Problem	0.0833	1.0000	0.0208	0.9995	0.0212	1.0000	0.0245
20	2301001	Abdominal Pain / Problems	0.0833	1.0000	0.0221	0.9990	0.0241	1.0000	0.0249
21	2301011	Back Pain / Non-Traumatic	0.0833	1.0000	0.0174	0.9999	0.0213	1.0000	0.0264
22	2301059	Psychiatric Problem / Abnormal Behavior / Suicide Attempt	0.0417	1.0000	0.0100	1.0000	0.0308	1.0000	0.0273
23	2301003	Allergic Reaction / Stings	0.0833	1.0000	0.0139	1.0000	0.0248	1.0000	0.0280
24	2301071	Transfer / Interfacility / Palliative Care	0.0833	1.0000	0.0278	0.9937	0.0586	1.0000	0.0325
25	2301069	Traffic / Transportation Incident	0.0833	1.0000	0.0308	0.9878	0.0466	1.0000	0.0334
26	2301057	Pregnancy / Childbirth / Miscarriage	0.1250	0.9942	0.0451	0.9317	0.0686	1.0000	0.0403
27	2301053	Overdose / Poisoning / Ingestion	0.1250	0.9942	0.0486	0.9127	0.1186	1.0000	0.0488
28	2301005	Animal Bite	0.0833	1.0000	0.0343	0.9784	0.0611	1.0000	0.0489
29	2301043	Heat / Cold Exposure	0.1667	0.9024	0.0712	0.7725	0.1382	1.0000	0.0548
30	2301063	Stab / Gunshot Wound / Penetrating Trauma	0.1667	0.9024	0.0729	0.7616	0.1651	1.0000	0.0550
31	2301007	Assault	0.1667	0.9024	0.0829	0.7008	0.2160	1.0000	0.0630
32	2301023	Choking	0.1250	0.9942	0.0846	0.6906	0.1343	1.0000	0.0714
33	2301081	Drowning / Diving / SCUBA Accident	0.1667	0.9024	0.1211	0.5074	0.1713	1.0000	0.0769

[a] Ranking is based on the Wasserstein distance to the reference pattern
[b] KS ≡ The two-sample Kolmogorov–Smirnov test (Massey, 1951; Boo et al., 2018).
[c] CVM ≡ The two-sample Cramér-von Mises test (Anderson, 1962).
[d] CS ≡ The Chi-Square goodness-of-fit test (Moore, 1986; Ross, 2014).
[e] The Wasserstein distance (metric) between two empirical cumulative distributions. This is also known as the *Earth Mover's distance* (Duda, 2018).

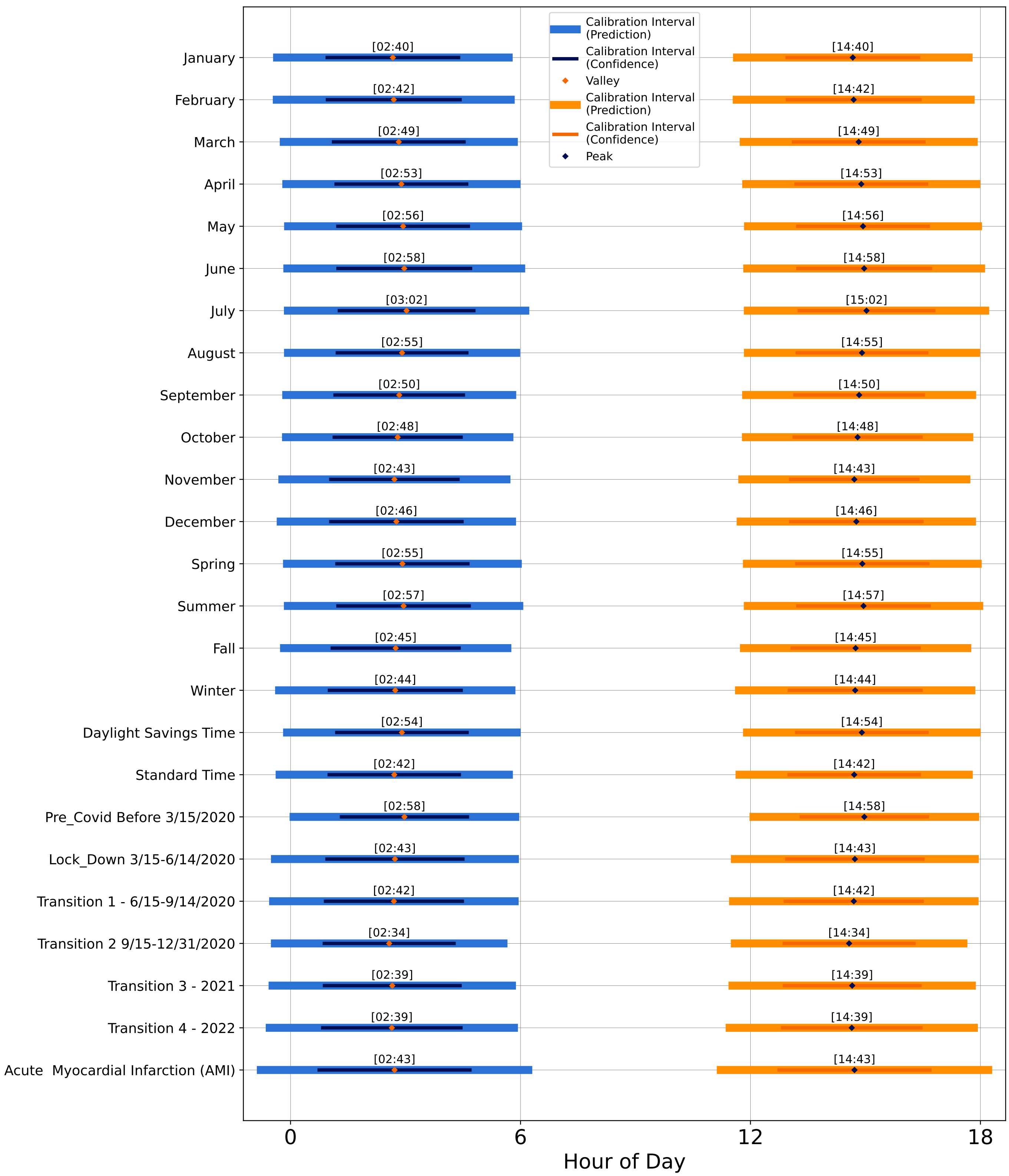


Figure 5: Peak and nadir times of day for the extended analyses, i.e. time periods (month, season, daylight savings/civil time, COVID-19 periods) and the AMI-specific pattern. The times are shown with calibrated intervals derived from the 95% prediction limits and 95% confidence intervals. The peak and nadir times are found via the first derivative of the fitted sinusoidal function for each type. Intervals are estimated using the standard error from the regression model.

Supplementary Material

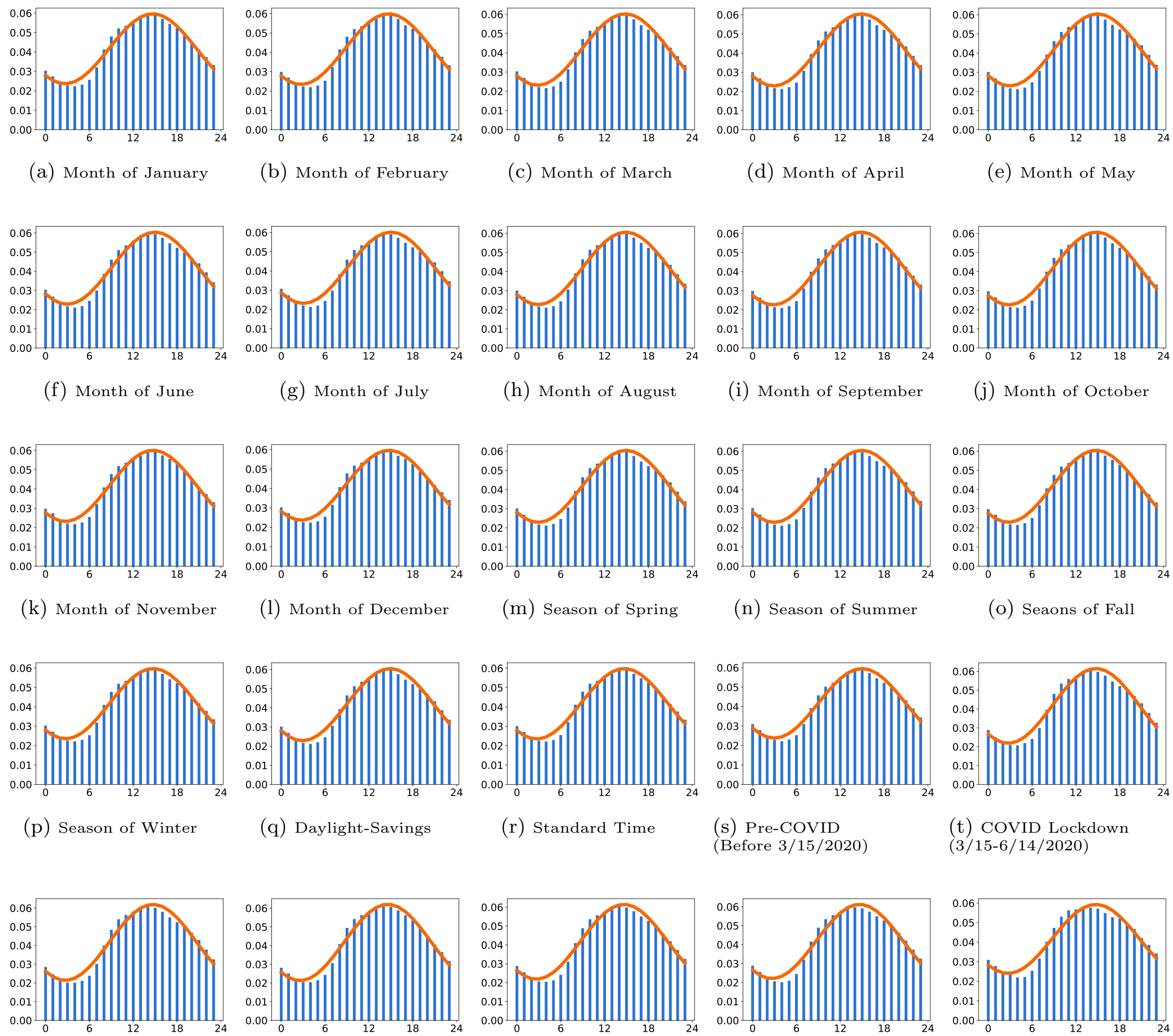
Table 7: List of the number of EMS activations captured in the NEMSIS Public Research data-set for years 2010-2022. Breakdown by extended analysis category.

Extended Analysis Category	Total Activations
January	26,042,149
February	23,650,098
March	25,507,966
April	24,845,265
May	26,630,458
June	25,968,185
July	27,750,866
August	27,497,144
September	25,978,081
October	26,838,051
November	25,061,405
December	26,078,782
Spring	77,580,355
Summer	81,343,585
Fall	77,497,596
Winter	75,426,914
Daylight Savings Time	205,341,884
Standard Time	106,506,566
Pre-Covid Before 3/15/2020	190,948,079
Lock-Down 3/15-6/14/2020	8,811,928
Transition 1 - 6/15-9/14/2020	10,080,698
Transition 2 9/15-12/31/2020	11,271,860
Transition 3 - 2021	43,434,044
Transition 4 - 2022	47,301,841
Acute Myocardial Infarction (AMI)	642,499

Table 8: Summary of sinusoidal regression results for the 25 cases in the extended analysis. All coefficients are statistically significant, most at the $p < 0.0001$ level. The coefficient of determination (R^2) was between 0.95 and 0.97 for all models, and root mean square error less than 0.003 for all models.

Extended Analysis Category	$\hat{\beta_0}$	95% Confidence Interval for $\hat{\beta_0}$	$\hat{\beta_1}$	95% Confidence Interval for $\hat{\beta_1}$	$\hat{\beta_2}$	95% Confidence Interval for $\hat{\beta_2}$	R^2	Adj. R^2	RSME
January	0.0417 ***	[0.0406 , 0.0427]	-0.0138 ***	[-0.0152 , -0.0123]	-0.0116 ***	[-0.013 , -0.0101]	0.9693	0.9664	0.0023
February	0.0417 ***	[0.0406 , 0.0427]	-0.0139 ***	[-0.0154 , -0.0124]	-0.0118 ***	[-0.0133 , -0.0103]	0.9681	0.9651	0.0023
March	0.0417 ***	[0.0406 , 0.0427]	-0.0137 ***	[-0.0152 , -0.0122]	-0.0125 ***	[-0.0140 , -0.0110]	0.9700	0.9672	0.0023
April	0.0417 ***	[0.0406 , 0.0427]	-0.0137 ***	[-0.0152 , -0.0122]	-0.0129 ***	[-0.0144 , -0.0114]	0.9700	0.9671	0.0023
May	0.0417 ***	[0.0406 , 0.0427]	-0.0135 ***	[-0.0150 , -0.0120]	-0.0131 ***	[-0.0146 , -0.0116]	0.9701	0.9672	0.0023
June	0.0417 ***	[0.0406 , 0.0428]	-0.0134 ***	[-0.0150 , -0.0119]	-0.0132 ***	[-0.0147 , -0.0116]	0.9682	0.9651	0.0024
July	0.0417 ***	[0.0406 , 0.0428]	-0.0130 ***	[-0.0146 , -0.0114]	-0.0132 ***	[-0.0148 , -0.0116]	0.9664	0.9632	0.0024
August	0.0417 ***	[0.0406 , 0.0427]	-0.0137 ***	[-0.0152 , -0.0122]	-0.0131 ***	[-0.0146 , -0.0116]	0.9709	0.9682	0.0023
September	0.0417 ***	[0.0406 , 0.0427]	-0.0141 ***	[-0.0155 , -0.0126]	-0.0129 ***	[-0.0144 , -0.0114]	0.9719	0.9693	0.0023
October	0.0417 ***	[0.0406 , 0.0427]	-0.0142 ***	[-0.0156 , -0.0128]	-0.0128 ***	[-0.0142 , -0.0113]	0.9731	0.9705	0.0022
November	0.0417 ***	[0.0407 , 0.0427]	-0.0140 ***	[-0.0154 , -0.0126]	-0.0120 ***	[-0.0134 , -0.0106]	0.9728	0.9702	0.0022
December	0.0417 ***	[0.0406 , 0.0427]	-0.0135 ***	[-0.0149 , -0.0120]	-0.0119 ***	[-0.0134 , -0.0105]	0.9694	0.9665	0.0023
Spring	0.0417 ***	[0.0406 , 0.0427]	-0.0136 ***	[-0.0151 , -0.0121]	-0.0130 ***	[-0.0145 , -0.0115]	0.9697	0.9668	0.0024
Summer	0.0417 ***	[0.0406 , 0.0427]	-0.0135 ***	[-0.0150 , -0.0119]	-0.0131 ***	[-0.0146 , -0.0116]	0.9694	0.9664	0.0024
Fall	0.0417 ***	[0.0407 , 0.0427]	-0.0141 ***	[-0.0155 , -0.0127]	-0.0124 ***	[-0.0138 , -0.0109]	0.9731	0.9706	0.0022
Winter	0.0417 ***	[0.0406 , 0.0427]	-0.0137 ***	[-0.0151 , -0.0122]	-0.0119 ***	[-0.0133 , -0.0104]	0.9689	0.9660	0.0023
Daylight Savings	0.0417 ***	[0.0406 , 0.0427]	-0.0136 ***	[-0.0151 , -0.0121]	-0.0130 ***	[-0.0145 , -0.0115]	0.9702	0.9674	0.0023
Standard Time	0.0417 ***	[0.0406 , 0.0427]	-0.0138 ***	[-0.0153 , -0.0124]	-0.0118 ***	[-0.0133 , -0.0104]	0.9704	0.9676	0.0022
Pre_Covid < 3/15/20	0.0417 ***	[0.0407 , 0.0426]	-0.0127 ***	[-0.0141 , -0.0114]	-0.0125 ***	[-0.0139 , -0.0112]	0.9739	0.9714	0.0021
Lock_Down ≤ 6/14/20	0.0417 ***	[0.0405 , 0.0429]	-0.0150 ***	[-0.0167 , -0.0133]	-0.0130 ***	[-0.0147 , -0.0113]	0.9650	0.9617	0.0027
Trans 1 - 6/15-9/14/20	0.0417 ***	[0.0404 , 0.0429]	-0.0154 ***	[-0.0172 , -0.0137]	-0.0132 ***	[-0.0149 , -0.0114]	0.9642	0.9608	0.0028
Trans 2 9/15-12/31/20	0.0417 ***	[0.0405 , 0.0428]	-0.0160 ***	[-0.0176 , -0.0143]	-0.0127 ***	[-0.0143 , -0.0111]	0.9707	0.9679	0.0025
Trans 3 - 2021	0.0417 ***	[0.0405 , 0.0429]	-0.0152 ***	[-0.0169 , -0.0135]	-0.0127 ***	[-0.0144 , -0.0110]	0.9653	0.9620	0.0027
Trans 4 - 2022	0.0417 ***	[0.0404 , 0.0429]	-0.0151 ***	[-0.0168 , -0.0133]	-0.0125 ***	[-0.0143 , -0.0108]	0.9627	0.9592	0.0027
Acute Myocardial Infarction	0.0417 ***	[0.0403 , 0.0430]	-0.0134 ***	[-0.0152 , -0.0115]	-0.0115 ***	[-0.0134 , -0.0096]	0.9484	0.9435	0.0029

*$p < 0{\cdot}01$ **$p < 0{\cdot}001$ ***$p < 0{\cdot}0001$; $R^2 \equiv$ coefficient of determination; RMSE ≡ root mean squared error.



(a) Month of January

(b) Month of February

(c) Month of March

(d) Month of April

(e) Month of May

(f) Month of June

(g) Month of July

(h) Month of August

(i) Month of September

(j) Month of October

(k) Month of November

(l) Month of December

(m) Season of Spring

(n) Season of Summer

(o) Seaons of Fall

(p) Season of Winter

(q) Daylight-Savings

(r) Standard Time

(s) Pre-COVID (Before 3/15/2020)

(t) COVID Lockdown (3/15-6/14/2020)

(u) COVID Transition 1 (6/15-9/14/2020)

(v) COVID Transition 2 (9/15-12/31/2020)

(w) COVID Transition 3 (1/1-12/31/2021)

(x) COVID Transition 4 (1/1-12/31/2022)

(y) Acute Myocardial Infarction (AMI)

Figure 6: Month of Daily patterns for 25 periods in the extended analysis, derived from sinusoidal regression. x-axis is the (military) hour of day. y-axis is the frequency (percent) of dispatch events in the hour. Blue bars are observations to form the 24-hour distribution, from 2010-2022 NEMSIS data. The red line is the fitted sinusoidal regression model. See equation 1 and its derivation in the Appendix.