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# The role of emergency incident type in identifying first responders' health exposure risks

**Emily J. Haas**[a,*], **Katherine N. Yoon**[a], **Alexa Furek**[a], **Megan Casey**[b], **Susan M. Moore**[a]

[a]National Personal Protective Technology Laboratory (NPPTL), National Institute for Occupational Safety and Health (NIOSH), Pittsburgh, PA 15236, United States

[b]National Personal Protective Technology Laboratory (NPPTL), National Institute for Occupational Safety and Health (NIOSH), Morgantown, WV 26505, United States

## Abstract

Fire-based emergency management service (EMS) personnel are dispatched to various incidents daily, many of which have unique occupational risks. To fully understand the variability of incident types and how to best prepare and respond, an exploration of the U.S. coding system of incident types is necessary. This study uses potential exposure to SARS-CoV-2 as a case example to understand if and how coding categories for incident call types may be updated to improve data standardization and emergency response decision making. Researchers received emergency response incident data generated by three fire department computer-aided dispatch (CAD) systems between March and September 2020. Each incident was labeled *EMS, Fire*, or *Other*. Of the 162,766 incidents, approximately 8.1% ($n$ = 13,144) noted potential SARS-CoV-2 exposure within their narrative descriptions of which 86.3% were coded as *EMS*, 9.9% as *Fire*, and 3.9% as *Other*. To assess coding variability across incident types, researchers used the original 3-incident type variable and a new 5-incident type variable reassigned by researchers into *EMS, Fire, Other, Hazmat,* and *Motor Vehicle*. Logit regressions compared differences in potential exposure using the 3- and 5-incident type variables. When evaluating the 3-incident type variable, those responding to a *Fire* versus an *EMS* incident were 84% less likely to be associated with potential exposure to SARS-CoV-2. For the 5-incident type variable, those responding to *Fire* incidents were 77% less likely to be associated with a potential exposure than those responding to *EMS* incidents. Changes in potential exposure between the 3- and 5-incident type models show the need to understand how incident types are assigned. This demonstrates the need for data standardization to accurately categorize incident types to improve emergency preparedness and response. Results have implications for incident type coding at fire department municipality and national levels.



*Corresponding author. wcq3@cdc.gov (E.J. Haas).

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Declaration of Competing Interest
The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

**Keywords**

Emergency medical services; Firefighter; Incident type; Surveillance; Telecommunicator

## 1. Introduction

The initial situation that fire station personnel, including those who provide fire-based emergency medical services (EMS), are presented with when dispatched to an event is referred to as an incident type. When telecommunicators receive emergency 9–1–1 calls, they conduct triage to describe the emergency and subsequently assign a code to each incident. This code assignment is termed *incident type* throughout this paper. It describes the scenario that these fired-based EMS personnel are expecting to be presented with when arriving at the scene. Codes applied to designate an incident type often adopt those defined by the National Fire Incident Reporting System (NFIRS) [1] and are ultimately recorded within department-specific computer-aided dispatch (CAD) systems.

Incident types can be valid indicators to identify health-related risks among personnel who respond to incidents, recognize hot-spot clusters, estimate demand and resources needed, and forecast the progression of epidemics [2-5]. However, the voluntary nature of NFIRS 5.0 and the use of different CAD software systems make consistent and reliable incident reporting across departments a challenge [6,7]. To illustrate, between NFIRS versions 4.1 and 5.0, the number of potential EMS incident types increased 314% from 7 sub-incident codes to 29 [1]. Related to the software systems that manage emergency calls, a survey conducted with a sample of 431 fire departments revealed the use of 35 unique CAD software vendors to record and manage call data [8].

According to Maguire and colleagues [9], the inability to correctly collect and interpret emergency response data is a critical barrier in public safety surveillance. The need for accurate incident-type coding, in addition to the need for consistent coding, has received recent attention. For example, one study found that dispatching errors due to inaccurate incident interpretation caused 9% of 9–1–1 calls to be rerouted [10]. In another study, a prioritization algorithm was applied to the Fire Department of New York's emergency 9–1–1 calls, revealing 63 incident types used to reflect medical or trauma emergencies [11]. The varying numbers of incident type options available have resulted in inconsistencies within and across municipality incident coding [12]. To illustrate, for the same event, one 9–1–1 telecommunicator may interpret the caller's description of an incident as chest pain. In contrast, another may interpret it as respiratory distress when the issue at hand is chest pain due to difficulty breathing. To this end, understanding the role that incident type may have in responders' occupational health risks serves not only as an impetus to improve data quality issues but can also inform decision making and planning at the department, state, and national levels.

### 1.1. Objectives

In the current study, researchers from the National Institute for Occupational Safety and Health (NIOSH) wanted to understand the consistency of incident types that are coded across fire department CAD systems. The objective was to study the instances of inconsistent coding using a case study that compared two incident-type coding approaches: an original 3-incident type as determined by the telecommunicator, and an adjusted 5-incident type coding determined by the researchers.

## 2. Material and methods

NIOSH collaborated with the International Public Safety Data Institute (IPSDI) [13] to receive 9–1–1 emergency call details (which include incident type coded for each call) from IPSDI's National Fire Operations Reporting System (NFORS). NFORS (which is a different system than NFIRS) links to either the CAD, the fire department's records management system (RMS), or both using an application programming interface, automatic creation, and ingestion of a file in CSV or XML format, or through other methods (depending on the CAD or RMS brand). For this study, data contained call details provided by three fire department's municipal CAD systems, each serving a population of more than 1 million people in Massachusetts, New York, and Ohio. This activity was reviewed by CDC and was conducted consistently with applicable federal law and CDC policy.[1]

### 2.1. Incident type codes

CAD systems attribute various data elements to each 9–1–1 call, such as incident description, incident type, response location and duration, resources deployed, weather, and other elements. This information is collected by the 9–1–1 telecommunicator who is on the phone. They enter information into the CAD based on a series of standard questions aimed at determining the nature of the incident. Based on the information collected by the 9–1–1 telecommunicator, this individual assigns the incident type, which often follows the classifications: *Fire* incidents include any indoor or outdoor fire or a fire alarm. *EMS, Fire*, and *Other*. *EMS* incidents vary and can entail any trauma or health event, such as a stroke or heart attack. Service calls, good intent calls, and false alarms are often coded as *Other* incident types.

Researchers used potential occupational exposure to SARS-CoV-2 that was accounted for in two different ways during 9–1–1 emergency incident calls, making this specific type of contagious emergency a clear case example to address the study objectives. First, *Contagious Emergency* incidents were added to municipal CAD systems as separate incidents. If an emergency call was made directly in response to difficulties a positive patient was experiencing, the incident was coded *Contagious Emergency*. The *Contagious Emergency* attribution allowed departments to easily filter for and track trends potentially driven by the COVID-19 pandemic across their local area. Specifically, the participating fire departments would code an incident as *Contagious Emergency* if keywords like RESD, coronavirus, COVID, flu, cov19, or corona were mentioned during the call. Eventually, when IPSDI normalized this dataset using a free text search, it became included as an *EMS* incident subtype, although it retained the *Contagious Emergency* narrative description.

[1]See e.g., 45 C.F.R. part 46; 21 C.F.R. part 56; 42 U.S.C. §241(d), 5 U.S.C. §552a, 44 U.S.C. §3501 et seq

Second, although not an incident type, during emergency calls, telecommunicators could glean, through a series of predetermined questions that were temporarily inserted as a part of their routine script, whether there was a potential for responders to be exposed to SARS-CoV-2. This was answered using a "Yes" or "No" indication as a separate data point in the emergency call log. Therefore, any emergency call that had an incident type of *Contagious Emergency* would also have a "Yes" for potential exposure to SARS-CoV-2 whereas another incident type *of EMS, Fire*, or *Other* could have a "Yes" or "No" for potential exposure based on caller responses to the routine questions asked.

### 2.2. Sample

From March to September 2020, NIOSH received NFORS data for 162,766 emergency call responses as described above, via a CVS file that was cleaned and transferred into statistical software for further analysis. Within the sample, 64.2% ($n$ = 104,468) were coded *EMS*; 29.6% ($n$ = 48,212) as *Fire*; and 6.2% ($n$ = 10,086) as *Other*. Of these incidents, 8.1% ($n$ = 13,144 incidents) noted potential exposures to SARS-CoV-2 based on information received during the call. Among these 13,144 potential exposures, 86.3% were *EMS* incidents; 9.9% were *Fire* incidents; and the remaining 3.9% were entered as *Other*.

Table 1 presents the percentages of *EMS, Fire*, and *Other* incident types that also noted a potential exposure to SARS-CoV-2 and the percentage of incidents coded as *Contagious Emergency*. Again, in these latter instances, the only box checked was *Contagious Emergency* and nothing else, such as a stroke. In the dataset, 4969 incidents were classified as *Contagious Emergency* at the onset of the 9–1–1 call. We ran models that kept these *Contagious Emergency* codes within their original *EMS* incident type delegation, but also completed analyses that excluded these 4969 cases.

### 2.3. Data cleaning and recoding of incident types

To initially understand the assignment of incident types among department dispatch codes, researchers consulted the raw data file to examine the corresponding open-ended narrative descriptions of each incident. After visually noting discrepancies, we completed a formal qualitative content analysis [14] of these narratives, revealing common systematic classifications and themes and obvious inconsistencies. There were approximately 165 unique narrative descriptions of incidents across the three departments, illustrating several differences in incident interpretation and subsequent coding assignments. Two researchers worked together to further discuss, agree upon, and manually recode (i.e., correctly label) the 162,766 incidents to mitigate inconsistencies. Examples of categories that we recoded were: (1) incident types coded as *Other* that were clearly *EMS* incidents (e.g., stroke, unconscious person) and (2) incident types where no one was hurt or treated (e.g., locking keys in car) that were coded as *EMS* or *Fire* rather than *Other*. Additional trends documented within the incident descriptions were also identified that prompted us to extract two incident types and create separate incident variables (i.e., *Hazmat* and *Motor Vehicle*).

**2.3.1. Hazmat incidents—**Hazmat incidents are specific conditions (with no fire) indicating that a hazardous material may be involved. Hazardous conditions occur less frequently but tend to have significant overlap between EMS and fire responses. Previously developed guidance states if incidents involved fire and EMS then *Fire* should be used [1]. However, the coding assignments for these three fire departments indicate that such guidance is not always followed. For our data, if narrative incident descriptions referenced hazardous materials, gas leaks, or odors, but no fire, it was recoded into a separate *Hazmat* incident variable.

**2.3.2. Motor vehicle incidents—**The most applicable incident code for motor vehicle accidents and incidents is still unclear [15]. According to the U.S. national incident type descriptions, a vehicle accident with no injuries may be considered *EMS*. Alternatively, a vehicle accident that results in flammable spills and leaks may initiate an *EMS, Fire,* or even *Other* incident-type categorization. Given the number of these incidents that occur and the lack of decisiveness in how they are coded (in the original dataset around 60% of motor vehicle accidents were coded as *Fire* and 40% as *EMS*), we created a separate motor vehicle incident variable. After recoding the incident descriptions, we created a new variable with these five incident types (*EMS, Fire, Other, Hazmat, Motor Vehicle*). See Table 2 for examples of incident descriptions that may fall into a respective incident type.

## 2.4. Logit regression

Researchers conducted general linear model (GLM) logistic analyses in R v 4.0.3. [16] Using the original 3-incident type (*EMS, Fire,* and *Other*) and the newly coded 5-incident type (*EMS, Fire, Other, Hazmat,* and *Motor Vehicle*) variables. Before completing the regressions, researchers added to the dataset as a control variable, the monthly average of new, confirmed COVID-19 cases (reported for the counties that each fire department served), in monthly aggregates using public data. These data were separate from the potential SARS-CoV-2 exposures reported in the NFORS dataset and were obtained from the New York Times GitHub public data source [17]. Controlling for the monthly average of new COVID-19 cases added within each county that participating fire departments served was desirable to more accurately know how and to what degree incident type may predict potential exposure to SARS-CoV-2. Additionally, county-level data was the lowest level of reporting available and is a good proxy for the incidence of COVID-19 for the municipalities that each fire department served.

Researchers used the original 3-incident type variable and the newly coded 5-incident type variable (coded by researchers) to complete Logit regression analyses. Each logistic regression tested whether incident type (3-type variable: *EMS, Fire*, and *Other*, 5-type variable: *EMS, Fire, Other, Hazmat,* and *Motor Vehicle*) was associated with potential exposure to SARS-CoV-2 controlling for state (i.e., fire department), season, total population (using Federal Information Processing Series (FIPS) codes), and the confirmed number of monthly reported COVID-19 cases by county added from the GitHub source previously referenced.

# 3. Results

## 3.1. Model 1 and model 2: including all NFORS data

Controlling for all variables previously discussed, Model 1 (3-incident type variable that includes all data from NFORS), shows that incident types coded as a *Fire* call versus an *EMS* call were 84% less likely to be associated with potential exposure to SARS-CoV-2 and *Other* incident types were 72% less likely to be associated with potential exposure to SARS-CoV-2 when compared to *EMS* calls. Adding time (season) as a dummy variable into the model did not significantly change the results.

In Model 2 (including all data from NFORS), the 5-incident type variable was tested. Controlling for all variables, results for Model 2 showed that incident type codes as a *Fire* call versus *EMS* call were 77% less likely to be associated with potential exposure to SARS-CoV-2 and for *Other* calls, responders were 80% less likely to be exposed compared to *EMS* calls. Responding to *Hazmat* and *Motor Vehicle* incidents also had less likelihood of exposure than *EMS* incidents.

Although increased exposure risk for EMS calls compared to the other incident types is not surprising, comparing the results from Model 1 to Model 2 shows unique differences in potential SARS-CoV-2 exposure risks for the other types of calls. Specifically, potential SARS-CoV-2 exposure increased by 8% for incident types coded as *Fire* calls and decreased by 8% for *Other* calls. This difference in exposure odds between Models 1 and 2 shows the variability of exposure risk when reclassifying (to correct) incident types.

## 3.2. Model 3 and model 4: excluding NFORS data that was coded contagious emergency

Researchers then completed the same analyses for the 3-incident type variable and 5-incident type variable with data excluding those incidents within the NFORS data that were only coded as a *Contagious Emergency*. In Model 3 (using the 3-incident type variable), the logistic regression showed that responding to a *Fire* incident versus an *EMS* incident was 78% less likely to be associated with potential exposure to SARS-CoV-2, controlling for the state, season, the total population, and confirmed COVID-19 cases included from GitHub. Note that Model 3 used the new dataset excluding incidents that were already coded as a *Contagious Emergency*; thus, the difference in potential exposure between *EMS* and *Fire* in Model 3 is lower than in Model 1.

In Model 4 (5-incident type variable), those responding to *Fire* incidents were 70% less likely to be associated with potential exposure to SARS-CoV-2 than when responding to *EMS* incidents. Responding to *Other, Hazmat*, and *Motor Vehicle* incidents had even less association with a potential exposure than *EMS* incidents. In comparing the results from Model 3 to Model 4, responders' association with potential exposure to SARS-CoV-2 increased by 8% during *Fire* calls and decreased by 10% for *Other* calls. This difference in potential exposure between Models 3 and 4 again shows the variability of exposure risk when reclassifying (to correct) incident types. In all models, total population, and averaged monthly COVID-19 cases by county from GitHub were positively associated with possible exposure, holding all other variables constant. See Table 3 for results from all four models.

# 4. Discussion

Like the effort outlined in the current study, previous research has tried to better understand, validate, or standardize 9–1–1 dispatch codes manually. In one study, researchers took an existing set of low-priority dispatch codes and derived a new list of 21 incident types that were integrated into dispatch protocols for one year. At the end of the year, 11 of these incident-type codes were validated and recommended as permanent for low-acuity responses [18]. Other studies have shown that certain incident types can predict negative health outcomes or supply and demand issues. For example, one study found that daily response incidents that were tagged as COVID-19 were strongly correlated with the eventual use of beds in intensive care units, informing supply and demand during subsequent pandemic waves [19]. Other studies have correlated certain incidents with personal protective equipment (PPE) demands during emergency responses [20-22]. For example, some responders may wear face shields over their existing mask or respiratory protection if a close patient encounter is expected. However, studies have not aimed to show the differences among incident type coding within the same dataset and what this may mean for associating responders' risks on the job.

Findings from previous research [18], as well as the current study, show that incident-type codes can be predictive, and that manual coding and in some cases recoding, can impact the accuracy of preparedness and response efforts. The current results also show the possibility of being inadequately prepared with insufficient people, PPE, or other resources if response data is not standardized. Further, results illustrate the value of data standardization and modernization to inform decision making during emergencies. Specifically, partnering across the EMS and fire services to make universal improvements to government and commercial surveillance systems provides the opportunity for greater precision in incident-type assignment, more robust modeling efforts, and subsequent response by personnel.

## 4.1. Implications for future incident type coding methodology

Based on differences in study results between the 3- and 5-incident type variables, *EMS* incident types can be further examined and perhaps reassessed to determine whether some of the sub-descriptions within them should be pulled out into their own "parent" incident type that could aid in decision making and resource allocation prior to a response. Additionally, as the coding was manually corrected, the potential risk of SARS-CoV-2 exposure for those responding to *Fire* calls increased while exposure risk during *Other* calls decreased. These changes indicate that incidents with more coding ambiguity, such as *Motor Vehicle Incidents*, where the coding split was 60% *Fire* and 40% *EMS* in the original 3-incident model, can impact accuracy. These results are important because any information that can be gleaned prior to arriving on the scene can help responders make more refined decisions in determining what equipment, supplies, and extra precautions they should take when responding to an emergency [23,24].

Results suggest that the accurate interpretation and coding of incident types can be improved. Generally, screening processes are completed by 9–1–1 telecommunicators, who use scripts and other guides to standardize data as much as possible. Although guidelines and protocols vary, there are public safety answering points and modified caller queries

(MCQ) that are often updated during disease outbreaks or emergency illnesses [25-29]. Although the 9–1–1 telecommunicator often conducts the emergency medical dispatch questioning, commercial ambulance services or EMS coordination centers may complete call screenings. They could use a different set of guidelines or protocols. Most recently, McCann et al. [23] have suggested recommendations to update MCQs to assist responder decision making in being able to adequately don the appropriate level of PPE prior to arriving on scene.

Even as more is learned about disease symptoms and screening tools are updated, there are still barriers related to the individual interpretation of each incident and its type. To illustrate, a national EMS database referenced by Unitek [30] compared 9–1–1 incident interpretations to the responding EMS's impressions of the patient's symptoms and condition and found a significant difference between the two. Similarly, the current study's results support varying interpretations among telecommunicators. Without clear guidance on what information triggers the use of a new code, telecommunicators may assess caller-provided details differently. To illustrate, Kinsey and Ahrens [15] found that, even among individuals with years of incident coding experience, agreement in incident assignments and final coding decisions of the narratives are not consistent. This issue of incident data reliability has been discussed previously [15] with recommendations for developing clearer coding guidance and using social science expertise to design future coding guidance. Moving forward, rather than try to repeatedly modify screening tools and data codes, more sophisticated data cleaning efforts, including artificial intelligence and machine learning, should be leveraged to aid data accuracy and subsequent decision making by fire-based EMS personnel.

### 4.2. Public safety data modernization

Fortunately, many agencies have promoted data modernization efforts, with the CDC supporting the movement away from siloed public health and safety surveillance systems to connected, resilient, adaptable, and sustainable systems that can predict and accurately respond to problems [31-34]. Machine learning to train models and recognize patterns within similar emergency response call scenarios has found that such methods can not only more accurately identify certain risks but may be faster [33]. Other studies have shown the value of machine learning methods to extract and label critical information from emergency incidents to assist in appropriate decision making on the dispatch side, eventually informing responders' decision making [35]. Using machine learning may help improve this identified gap in data standardization. The current national incident reporting system defined earlier [1] relies on a highly heterogeneous volunteer reporting strategy which includes possible variables that are not universally reported across departments or systems, resulting in a high reporter burden and low data useability. Thus, incident-type codes not only need to be standardized but also agile enough to minimize reporter burden.

Of course, small scale studies can occur first to assess the utility of machine learning for this problem. A possible pilot effort to explore the accuracy and utility of machine learning could include fire-based EMS responders temporarily completing a short report post response. This write up could then be compared and used to help identify and code an accurate call type based on the actual findings on the scene. Applying these data using a small-scale machine learning strategy may help identify if key indicators selected by personnel, such as chest pain, are confirmed through the final patient care report that is completed. If this triangulated effort yields high accuracy, additional machine learning methods could be deployed to effectively identify specific incident types beyond *EMS, Fire,* and *Other* to be more accurate (i.e., the researcher's 5-incident type variable) and provide recommendations to optimize and standardize a surveillance reporting system for greater usability. It is possible that combining emergency response data from several departments can create holistic machine learning models to train, test, and ultimately support telecommunicators during the coding of incident types. Future research should be explored in this area, particularly during the COVID-19 pandemic when new protocols were initiated and consistently updated [23].

### 4.3. Limitations

Although the results of our study illustrate the potential for data standardization and the need for more accurate coding to improve emergency planning, some limitations must be considered. First, potential exposure to SARS-CoV-2 was only used as an illustrative case example in the current study and, although not the purpose of this paper, is subject to limitations as the interpretation of the incident is assigned by telecommunicators, and it is unknown if these potential exposures resulted in a COVID-19 diagnosis. The emergency medical dispatch personnel were likely using standardized questions to identify potential COVID-19 incidents, such as the Emergency Infectious Disease Surveillance Tool for COVID-19 [36]. Although these tools performed moderately well at the onset of the pandemic, sensitivity and specificity of telephonic screening for COVID-19 were 75% and 46%, respectively [23]. Therefore, it is likely that the accuracy of the designation of a potential SARS-CoV-2 exposure in the current dataset was limited. Researchers controlled for confirmed, monthly COVID-19 cases by fire department county to help account for this limitation.

Similarly, incident descriptions are entered based on the individual telecommunicator, who may interpret and record things differently than other telecommunicators. It is unknown if these incident descriptions are updated after a response has been completed and the incident type is assigned. It is likely that if there was no definitive root cause as to what was wrong during the initial incident response, it was coded in one category and never updated to reflect the diagnosis after the responding units arrived at the scene. However, these differences in interpretation make the need for accurate coding even more important to ensure consistency in surveillance both nationally and internationally.

## 5. Conclusions

As previously indicated, voluntary standards exist to code emergency response incident types. However, the increase in incident-type coding options has served as an impetus to further consider data quality issues. This study aimed to understand the nuances of incident types and how the assignment of incident type codes could be improved to function as an emergency planning tool. Despite the current study's limitations, these results show the need and potential ability to improve the standardization, validity, and reliability of public safety surveillance data in fire services. With numerous data elements and inconsistent reporting guidelines, it is not practical to suggest data standardization in one study or paper. However, it is possible to begin exploring which data elements are most informative.

Moving forward, future studies should examine subsets of *EMS* incident types such as poisoning/overdose instances, suicide attempts, and other higher-frequency incidents to see if the results change other types of contaminant exposure probability as it did in the current study for *Motor Vehicle* incidents and the association with potential exposure to SARS-CoV-2. Subsets of *Fire* incidents should also be further examined to identify calls that may place responders at greater exposure risks. For example, tracking the potential presence of lithium-ion batteries is a significant hazard that first responders face and could inform preparedness efforts going into a response scenario. As additional *EMS* and *Fire* incident types are analyzed individually, perhaps research can identify the scenarios in which responders face the highest risk of occupational exposures. Finally, these results demonstrate the importance not only of individual interpretation of incident descriptions but also the value of developing algorithms to improve emergency management and response.

In summary, this study provides implications for future data modernization efforts to improve how incident types are classified within these already-established data reporting systems and suggest the need for nationwide data standardization to more accurately identify specific risks that fire station personnel may encounter. Such standardization provides a pathway for robust modeling efforts with greater confidence in future models. With greater confidence, these models may then be used to reveal a more refined, accurate incident coding system to be executed nationally.

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## Abbreviations:

| | |
|---|---|
| **EMS** | Emergency medical services |
| **NFIRS** | National Fire Incident Reporting System |
| **NFORS** | National Fire Operations Reporting System |
| **IPSDI** | International Public Safety Data Institute |
| **NIOSH** | National Institute for Occupational Safety and Health |
| **CAD** | computer-aided dispatch |

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## Table 1

Descriptive characteristics of incidents.

| | All incidents classified as potential exposure to SARS-CoV-2 | | | Excluding incidents that were classified as *Contagious Emergency*[1] | | |
|---|---|---|---|---|---|---|
| | **Total Incidents by Category** | **Counts of potential exposure to SARS-CoV-2 within categories** | **Percent (%)** | **Total Incidents by Category** | **Counts of potential exposure minus Contagious Emergencies** | **Percent (%)** |
| Incident type (3 categories) | | | | | | |
| *EMS* | 104,468 | 11,340 | 10.9% | 99,499 | 6371 | 6.4% |
| *Fire* | 48,212 | 1296 | 2.7% | 48,212 | 1296 | 2.7% |
| *Other* | 10,086 | 508 | 5.0% | 10,086 | 508 | 5.0% |
| Incident type (5 categories) | | | | | | |
| *EMS* | 112,247 | 11,803 | 10.5% | 107,278 | 6834 | 6.4% |
| *Fire* | 33,298 | 1100 | 3.3% | 33,298 | 1100 | 3.3% |
| *Other* | 3906 | 141 | 3.6% | 3906 | 141 | 3.6% |
| *Hazmat* | 2708 | 37 | 1.4% | 2708 | 37 | 1.4% |
| *Motor vehicle* | 10,607 | 63 | 0.6% | 10,607 | 63 | 0.6% |
| Season | | | | | | |
| *Spring (Mar-May)* | 63,905 | 7270 | 11.4% | 61,119 | 4484 | 7.3% |
| *Summer (Jun-Aug)* | 74,876 | 4954 | 6.6% | 73,065 | 3143 | 4.3% |
| *Fall (Sep)* | 23,985 | 920 | 3.8% | 23,613 | 548 | 2.3% |
| Fire Department state | | | | | | |
| *Massachusetts* | 42,596 | 3242 | 7.6% | 42,596 | 3242 | 7.6% |
| *New York* | 5693 | 1338 | 23.5% | 5693 | 1338 | 23.5% |
| *Ohio* | 114,477 | 8564 | 7.5% | 109,508 | 3595 | 3.3% |
| Total | 162,766 | 13,144 | | 157,797 | 8175 | |

[1] Note that Columbus Division of Fire, Ohio was the only fire department that implemented this *contagious emergency* category coding and thus, was the only department that had *EMS* incidents with potential SARS-CoV-2 exposure. Researchers analyzed the data without Columbus Division of Fire, Ohio and found very similar results: For the 3-incident type (model 3), OR for *Fire* was 0.3059 and *Other* 0.4440 and for the 5-incident type (model 4), OR for *Fire* was 0.4117, *Other* 0.3244, *Hazmat* 0.1761, and *Motor Vehicle* 0.1405 respectively and all were statistically significant. Researchers decided to report all cases including Ohio cases while controlling for fire department.

**Table 2**

Incident recoding with new incident variables and sub-descriptions. (*The sub-descriptions are provided to help provide the context of how incidents are described).*

| Recoded Incident Types with Example Subtypes | Example of Original Incident Sub-Description |
|---|---|
| 1. ***Fire*** | |
| Outdoor fire | Grass fire; out fire; brush/rubbish/grass fire/; trash fire |
| Structure fire | Fire – high rise; structural related fire |
| Other fire | Township fire; electrical fire assignment |
| Misc. alarms specified | Water flow alarm; carbon monoxide alarm; elevator alarm; fire alarm |
| 2. ***Motor Vehicle (new)*** | |
| Motor vehicle accident | Vehicle struck structure; auto accident entrapment; vehicle accident |
| Motor vehicle incident | Motor vehicle fire; vehicle accident involving fire |
| 3. ***Hazmat (new)*** | |
| Hazmat/bomb/gas | Hazardous condition or materials; bomb response; investigate odor; natural gas leak |
| 4. ***EMS*** | |
| Overdose/poison control | Poisoning; poisoning/overdose; conscious overdose; unconscious overdose |
| Bodily pain/reaction | Back pain; eye injury; burns; injured from fall; allergic reaction; animal bite |
| Trauma/injury | Injured from assault; trauma; advanced life support; person down |
| Emergency illness | Stroke; seizure; difficulty breathing; medical emergency |
| Suicide attempt/psychological | Suicide attempt; attempt – jumping; psychiatric problems |
| Contagious emergency | COVID-19 or symptoms of COVID-19 |
| 5. ***Other Incidents*** | |
| Public service assistance | Advice asked for; canine search; service; good intent call; lockout/lock in |

## Table 3

Logit analysis results.

| Independent Variables | Model 1 Odds Ratio [CI 95%] (all cases) | Model 2 Odds Ratio [CI 95%] (all cases) | Model 3 Odds Ratio [CI 95%] (without *Contagious Emergency* incidents) | Model 4 Odds Ratio [CI 95%] (without *Contagious Emergency* incidents) |
|---|---|---|---|---|
| T as(intercept) | 0.046 [0.042, 0.051] | 0.035 [0.032, 0.038] | 0.041 [0.037, 0.046] | 0.032 [0.029, 0.036] |
| Call Type (3) | | | | |
| *EMS* | ref | | ref | |
| *Fire* | 0.164 [0.154, 0.175] | | 0.217 [0.202, 0.232] | |
| *Other* | 0.282 [0.256, 0.311] | | 0.346 [0.313, 0.383] | |
| Call Type (5) | | | | |
| *EMS* | | ref | | ref |
| *Fire* | | 0.234 [0.219, 0.250] | | 0.304 [0.283, 0.326] |
| *Other* | | 0.206 [0.172, 0.245] | | 0.254 [0.211, 0.304] |
| *Hazmat* | | 0.096 [0.068, 0.131] | | 0.129 [0.091, 0.177] |
| *Motor vehicle* | | 0.050 [0.039, 0.064] | | 0.078 [0.060, 0.099] |
| State | | | | |
| *Massachusetts* | ref | ref | ref | ref |
| *New York* | 1.520 [1.396, 1.654] | 2.068 [1.901, 2.248] | 1.508 [1.384, 1.643] | 1.972 [1.810, 2.146] |
| *Ohio* | 0.526 [0.501, 0.553] | 0.693 [0.662, 0.726] | 0.235 [0.222, 0.249] | 0.299 [0.284, 0.316] |
| Total population[a] | 1.00003 [1.00002, 1.00004] | 1.00003 [1.00002, 1.00004] | 1.00003 [1.00002, 1.00004] | 1.00003 [1.00002, 1.00004] |
| Monthly average of COVID-19 by county[a] | 1.004 [1.003, 1.004] | 1.004 [1.003, 1.004] | 1.004 [1.004, 1.005] | 1.004 [1.004, 1.005] |
| Season[b] | | | | |
| *Fall (Sept)* | ref | ref | ref | ref |
| *Spring (Mar-May)* | 3.428 [3.193, 3.684] | 3.382 [3.150, 3.634] | 2.704 [2.467, 2.970] | 2.671 [2.437, 2.934] |
| *Summer (June-Aug)* | 1.824 [1.697, 1.962] | 1.813 [1.687, 1.950] | 1.975 [1.802, 2.169] | 1.958 [1.787, 2.150] |
| Sample size | 162,766 | 162,766 | 157,797 | 157,797 |

[a] Total population and monthly average COVID-19 by county are continuous variables. The odds ratios are to be interpreted without reference group. All other variables are categorical.

[b] Season was assigned as the following: Spring: March–May; Summer: June–August; Fall: September. Seasonal data is not cumulated, but is the count of incidents for each season, meaning we have more data points for Spring and Summer than for Fall. In this table, logit does not use accumulated data, we just have more datapoints for Spring/Summer than Fall.