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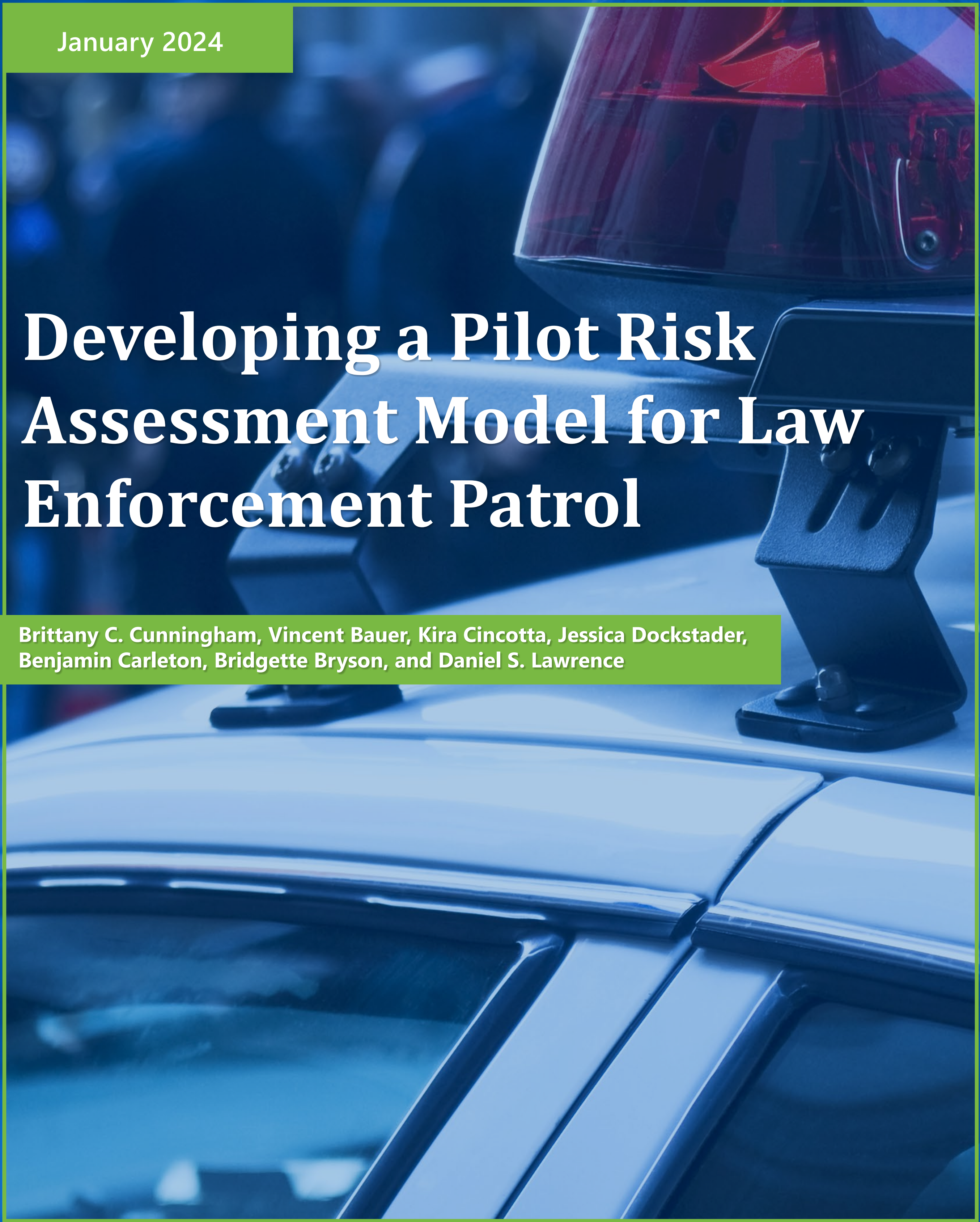

Developing a Pilot Risk Assessment Model for Law Enforcement Patrol

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This report is a product created through the ***Using Analytics to Improve Officer Safety*** project, a partnership between the Bureau of Justice Assistance and the CNA Center for Justice Research and Innovation**.** The work examines granular incident data during 2015–2019 from several local law enforcement agencies to identify incident characteristics (characteristics specific to the incident and related to officer tactical response) associated with officer assaults, injuries, and line-of-duty deaths. Using machine learning techniques, the project aims to produce a risk assessment model to link incident characteristics with officer safety outcomes. This work also entails collaborating with participating agencies to identify practices and recommendations to reduce risks to officer safety in the line of duty.

This document contains the best opinion of CNA at the time of issue.

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EXECUTIVE SUMMARY

Officer safety is of critical importance in an era of increased risk for law enforcement officers (hereinafter "officers"). Officers respond to some of the most unpredictable, traumatic, and violent encounters of any profession.[1] Although much of an officer's workday entails repetitive interactions, some calls for service or self-initiated contacts by officers may escalate into dangerous encounters. For officers to adequately mitigate the risks they may encounter while responding to calls for service, they must be well informed regarding the types of risks they face, the situations that may pose greater risk, and the strategies that will mitigate these risks.

The Using Analytics to Improve Officer Safety project examines calls for service data from ***2015 to 2019*** *from four local law enforcement agencies—the Camden County, New Jersey, Police Department; Columbia, South Carolina, Police Department; Houston, Texas, Police Department; and Spokane, Washington, Police Department*[2]*—to estimate factors related to high-risk incidents and identify drivers of officer injuries.*

Although previous empirical work on officer safety has yielded many important insights, to our knowledge, no prior work has applied machine learning models to produce risk assessments to promote officer safety. This project explored the potential for machine learning to identify high-risk incidents to officers using only the information available to dispatchers. A risk assessment model that could successfully flag high-risk incidents at dispatch would be immensely useful to law enforcement agencies, making it possible for officers to be better informed about potential risk factors before arriving on scene. Such a model would also be useful to agencies as they decide how to allocate scarce resources, such as deciding which calls should receive single- or dual-officer vehicles, where to send alternative response teams, and whether to deploy specialized units.

Readers should be aware that the model reflects the data upon which it is built. Biases in reporting and collecting officer injuries, as well as in how officers respond to calls for service, will be mirrored in the model's risk assessments. While we have gone to great lengths to build the model using objective factors, these biases could sometimes lead the model to identify a situation as high risk when in fact that situation reflects low risk to officers. Concerns about the potential for bias in machine learning are important to evaluate, and these techniques offer opportunities for objective empirical examination of divisive topics to minimize the bias that is already present in the real world.

Calls for service and Law Enforcement Officers Killed and Assaulted (LEOKA) data were merged from each of the four agencies, revealing the following findings:

- Overall, the machine learning model performed well, correctly identifying officer injuries about half of the time. Given the rarity of officer injuries within the four agencies, being able to identify half of such rare situations is notable.
- The model was also able to identify the factors that were the most important in predicting risk to officer safety and the types of incidents that posed the highest risk to officer safety. The results demonstrate that such a model can identify officer injuries from data on call characteristics; thus, whether such a model could be built into the dispatch process should be explored so that officers would be informed about potential risk factors before arriving at the location of a call.
- The model highlighted factors and calls for service types that posed greater risks to officer safety.
- The results of the machine learning model, along with the results from the officer interviews and surveys, also highlighted an often-overlooked aspect of police operations that is critically important to officer safety: dispatch.

Beyond producing statistical models, this project also collaborated with participating agencies to explore officer perspectives on safety and identify promising practices and recommendations to reduce risks to officers.

This project provides several practical benefits for improving officer safety. These benefits include the following:

- Quantifying concepts that until now have been only informally or qualitatively understood (e.g., the relative risks of different calls for service types).
- Comparing officer perceptions about injury risk to the quantitative data and identifying where gaps in understanding exist.
- Highlighting the important relationship between dispatch and patrol, as well as the implications that this relationship has for officer safety.
- Helping agencies assess the efficacy of their trainings and policies that directly affect officer safety.
- Providing guidance on the information agencies collect and make available to dispatchers.
- Supporting agencies to improve the amount and quality of risk and injury data agencies collect and use.

We hope that by providing agencies with a foundational knowledge of risks to officer safety, agencies will have a basis for modifying policy, training, and operations, leading to the implementation of strategies, processes, and procedures to keep officers and the communities they serve safe.

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INTRODUCTION

Officer safety is of critical importance in an era of increased risk for law enforcement officers (hereinafter "officers"). Officers respond to some of the most unpredictable, traumatic, and violent encounters of any profession.[3] Although much of an officer's workday entails repetitive interactions, some calls for service or interactions initiated by officers may escalate into dangerous encounters. Regardless of how officer injuries occur, the consequences are tragic and complex, affecting officers' work and home lives.[4]

> *For officers to adequately mitigate the risks they may encounter while responding to calls for service, they must be well informed regarding the types of risks they face, which situations may have higher risk, and the strategies that will mitigate these risks.*

The **Using Analytics to Improve Officer Safety** project examines calls for service data from 2015 to 2019 from four local law enforcement agencies—the Camden County, New Jersey, Police Department; Columbia, South Carolina, Police Department; Houston, Texas, Police Department; and Spokane, Washington, Police Department—to estimate factors related to high-risk incidents and identify drivers of officer injuries. Although previous empirical work on officer safety has yielded many important insights, to our knowledge, no prior work has applied machine learning models to produce risk assessments to promote officer safety. This project explores the potential for machine learning to identify high-risk incidents to officers using only the information that would be available to dispatchers. A risk assessment model that could successfully flag possible high-risk incidents at dispatch would be immensely useful to law enforcement agencies (hereinafter "agencies"), making it possible to better inform officers about potential risk factors before arriving on scene. Such a model would also inform agency decisions about how to allocate scarce resources, such as whether to respond with single- or dual-officer vehicles, when to send alternative response teams, and whether to deploy specialized units. Beyond producing statistical models, we also collaborated with participating agencies to explore officer perspectives on safety and to identify promising practices and recommendations to reduce risks of officer injuries. This report summarizes the development and outcomes of four agency-specific pilot risk assessment models; highlights officer perspectives on risks and response, training, and dispatch; and provides recommendations for promoting officer safety related to tactical preparedness.

This project provides several practical benefits for improving officer safety. These benefits include the following:

- Quantifying concepts that until now have been only informally or qualitatively understood (e.g., the relative risks of different calls for service types).
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- Highlighting the important relationship between dispatch and patrol, as well as the implications that this relationship has for officer safety.
- Helping agencies assess the efficacy of their trainings and policies that directly affect officer safety.
- Providing guidance on the information agencies collect and make available to dispatchers.
- Supporting agencies to improve the amount and quality of risk and injury data agencies collect and use.

DATA COLLECTION

Calls for service and LEOKA data

We produced **four agency-specific pilot risk assessment models** using the calls for service and Law Enforcement Officers Killed and Assaulted (LEOKA) officer injury data from the project agencies. The analysis examined over three million calls for service from these agencies with slightly more than 1,000 injuries to officers ranging from minor (e.g., bruised) to serious (e.g., hospitalization). The aggregated risk of officers receiving an injury while responding to a call for service in these four agencies was less than 0.03 percent, or about one injury per 3,500 calls for service.

Although important progress is being made in standardizing how data are collected and recorded across police agencies (such as the Federal Bureau of Investigation [FBI] Uniform Crime Reporting Program, Bureau of Justice Assistance [BJA] Justice Counts initiative), the type and detail of the information the project agencies had available for analysis differed. For our analysis, we standardized the data, to the extent possible, across the four agencies. Because so little is known by officers at the time of dispatch, most of the information we compiled describes the situation around the call. Some of the information we collected, such as data on weather conditions and census tract characteristics, came from secondary sources that would easily be available to any agency.

We generated 81 variables conceivably known by dispatch while receiving a call for service. These variables fell into seven categories:

1. **Call for service type:** the specific characteristics or qualities of a call for service (e.g., domestic violence, suspicious person, assault). The project agencies all categorized calls for service differently, so we generated a common schema with 22 categories.

2. **Date and time:** information about the hour, day of week, month, and year in which the incident took place, which allows the model to identify any temporal or seasonal patterns.

3. **Initiation type:** whether a community member or an officer initiated the call for service.[5]

4. **Weather conditions:** several variables related to the weather conditions on the day that the incident took place, including snow, rain, temperature, and the presence of fog. Information on the weather conditions in the precise location and at the precise time would be preferable to daily values but was not readily accessible. We generated weather conditions using the National Oceanic and Atmospheric Administration's (NOAA) Global Surface Summary of the Day.

5. **Local trends:** counts of the number of injuries, arrests, and incidents within the past 30, 90, and 180 days in the same beat, same district, and across the agency. Local patterns of activity may be important predictors of how a particular call for service will transpire.

6. **Location details:** number of days since the last injury, arrest, or call for service at the same location, since repeated calls to the same address may be a risk factor. Other details, such as whether an address was a residential or commercial property, would be useful in future models but were not readily available from all our project agencies.

7. **Census tract:** information on housing vacancies, employment, population density, and race in the census tract that the call for service took place in, using data from the 2010 Census. Neighborhood characteristics[6] raise important questions about fairness but may also be important predictors of officer injuries.

Interviews

Our team conducted semi-structured interviews with agency personnel from project agencies to better understand risks to officer safety. This included gathering perspectives from patrol officers, command staff, and training coordinators on identification of high-risk incidents, mitigation of risks, communication between officers and dispatch prior to and on scene, and officer safety training. We conducted between four and eight interviews for each agency. Each interview included a law enforcement subject expert as an interviewer to ensure comfortability and relatability.

We developed thematic codes for analyzing the interview responses, using both deductive and inductive coding approaches. Using the deductive approach, we pulled themes focused on assessment objectives from the interview protocols. Once we generated the list of codes, we reviewed the themes and definitions prior to coding the interviews. Using the inductive approach, we coded emergent themes to sub themes as we analyzed interview transcripts.

Surveys

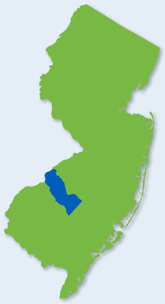
We administered an online survey to all project agency patrol personnel to gather input and feedback on officer safety and related topics, including identifying high-risk calls for service, attitudes on equipment and safety, and perspectives and experience with injuries. In addition, patrol personnel provided written responses regarding suggestions for improvement or recommendations on the topics mentioned above.

Our process for administering the survey was guided by the Dillman Tailored Design Survey Methodology (2014), an evidence-based practice in survey administration. This is a tested and trusted methodology for obtaining high survey response rates across a number of survey mediums, including paper, mail, and online.

In following the Dillman Tailored Design, we administered the surveys via CHECKBOX™, an online survey tool that allows for the administration and analysis of large-scale surveys and in this case ensured respondent confidentiality. Agency command staff sent an introductory email to all patrol personnel on the day of survey release with the embedded link to the survey. We assisted in sending out reminders to all patrol personnel during the three-week period the survey was live.

RESULTS FROM PROJECT AGENCIES

Camden County Police Department, New Jersey

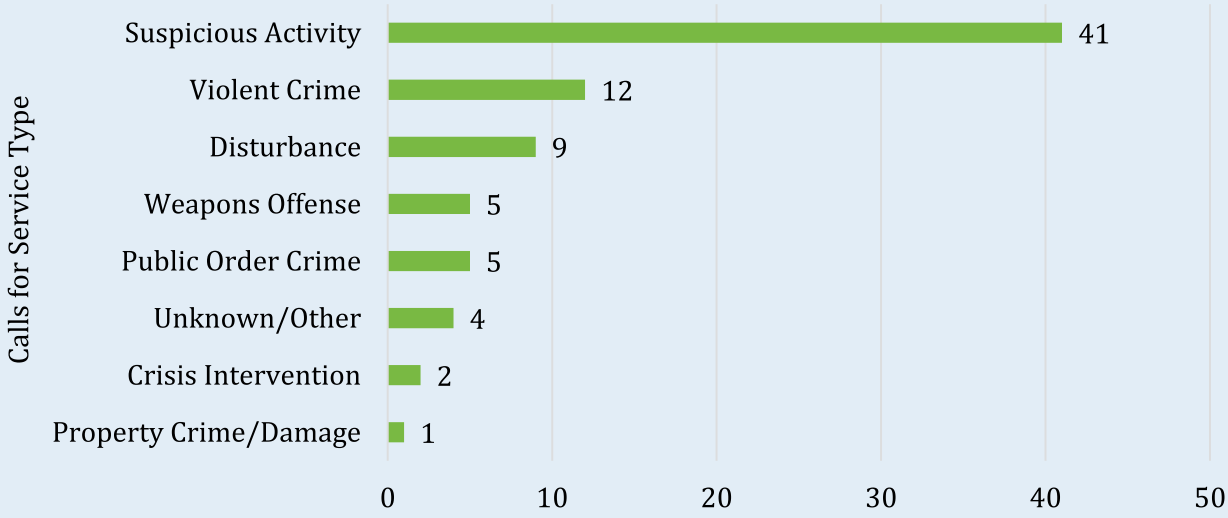


The Camden County Police Department (CCPD) is the primary provider of law enforcement services to the City of Camden, New Jersey. The City of Camden is located directly across the Delaware River from Philadelphia, Pennsylvania, and has an estimated population of 73,562.[7]

Overall, officer injuries during calls for service in CCPD are very rare, based on the calls for service analyzed. Of the 494,203 calls for service from 2015 to 2019, only 178 (0.04 percent) resulted in an officer injury. The officer injury data for CCPD include injuries sustained during physical altercations and foot pursuits. Additionally, the injuries analyzed represent only those for which we could match the agency's LEOKA data to the corresponding call for service entries. Of the 178 officer injuries, only 79 could be matched to the corresponding call for service entry and thus used in the analysis. As noted earlier in this report, because dangerous situations extend beyond instances in which an officer was injured, we also analyzed calls for service in which a suspect resisted arrest (1,892 calls for service) or possessed a weapon (4,238 calls for service).

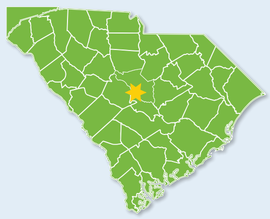
Figure 1 displays the number of calls for service that resulted in an officer injury between 2015 and 2019 by call for service type. Suspicious activity calls were the highest percentage (41 calls for service, 51.9 percent) of all calls for service resulting in an officer injury, followed by violent crime calls (12 calls for service, 15.2 percent) and disturbance calls (9 calls for service, 11.4 percent).

Figure 1. Calls for service resulting in officer injuries in Camden County Police Department, New Jersey: 2015–2019



Source: Calls for service data provided by Camden County (NJ) Police Department.

Columbia Police Department, South Carolina

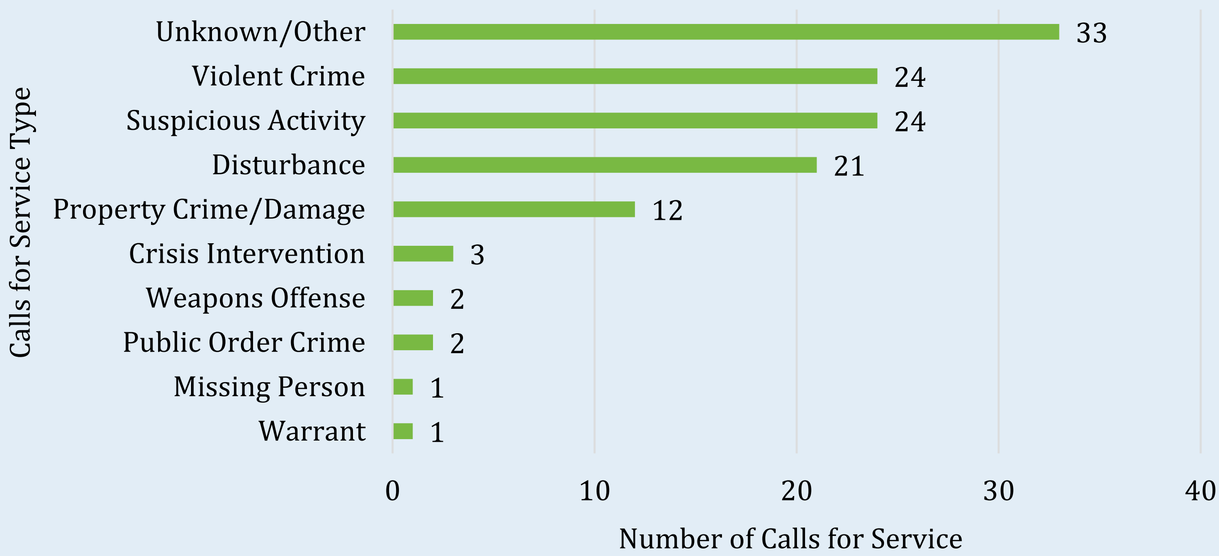


The Columbia Police Department (CPD) is one of the main public safety entities for the City of Columbia, South Carolina. Columbia is the state's capital and the second largest city in South Carolina, with an estimated population of 131,674.[8]

Based on the calls for service analyzed, officer injuries on calls for service in the CPD are rare. Of 772,920 calls for service from 2015 to 2019 analyzed, only 123 (0.02 percent) resulted in an officer injury. Given that dangerous situations extend beyond instances in which an officer was injured, we also analyzed calls for service in which a suspect resisted arrest (910 calls for service) or possessed a weapon (3,440 calls for service).

Figure 2 displays the number of calls for service that resulted in officer injuries between 2015 and 2019 by calls for service type. Between 2015 and 2019, unknown/other accounted for 33 (27 percent) of calls for service resulting in an officer injury, violent crime and suspicious activity accounted for 24 calls each (20 percent each), and disturbance calls accounted for 21 calls (17 percent).

Figure 2. Calls for service resulting in officer injuries in Columbia Police Department, South Carolina: 2015–2019



Source: Calls for service data provided by Columbia (SC) Police Department.

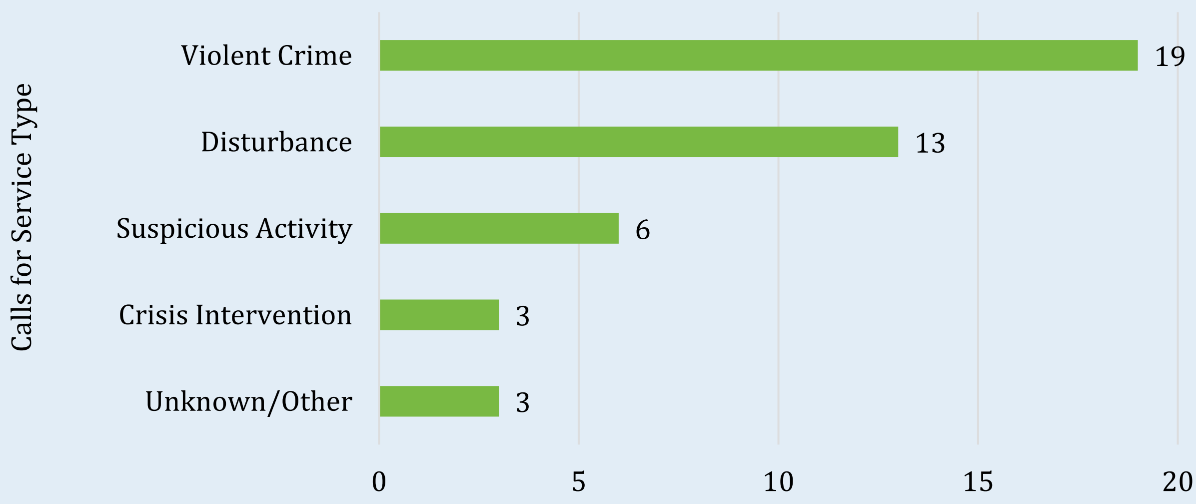
Spokane Police Department, Washington

The Spokane Police Department (SPD) is the main public safety entity for the City of Spokane, Washington. Spokane is the second highest populated city in Washington, with an estimated population of 228,989.[9]

Based on the calls for service analyzed, officer injuries on calls for service in the SPD are rare. Of 155,620 calls for service from 2017 to 2019,[10] only 44 (0.02 percent) resulted in an officer injury. Given that dangerous situations extend beyond instances in which an officer was injured, we also analyzed calls for service in which a suspect resisted arrest (478 calls for service) or possessed a weapon (541 calls for service).

Figure 3 displays the number of calls for service that resulted in officer injuries between 2017 and 2019 by calls for service type. Between 2017 and 2019, violent crime calls for service accounted for 19 total calls for service resulting in officer injuries (43 percent), with disturbances accounting for 13 calls for service (30 percent). Suspicious activity calls for service (6 calls) accounted for almost 14 percent of calls for service resulting in officer injuries, with both crisis intervention and unknown/other calls for service (3 calls each) each accounting for 7 percent of calls for service resulting in officer injuries.

Figure 3. Calls for service resulting in officer injuries in Spokane Police Department, Washington: 2017–2019



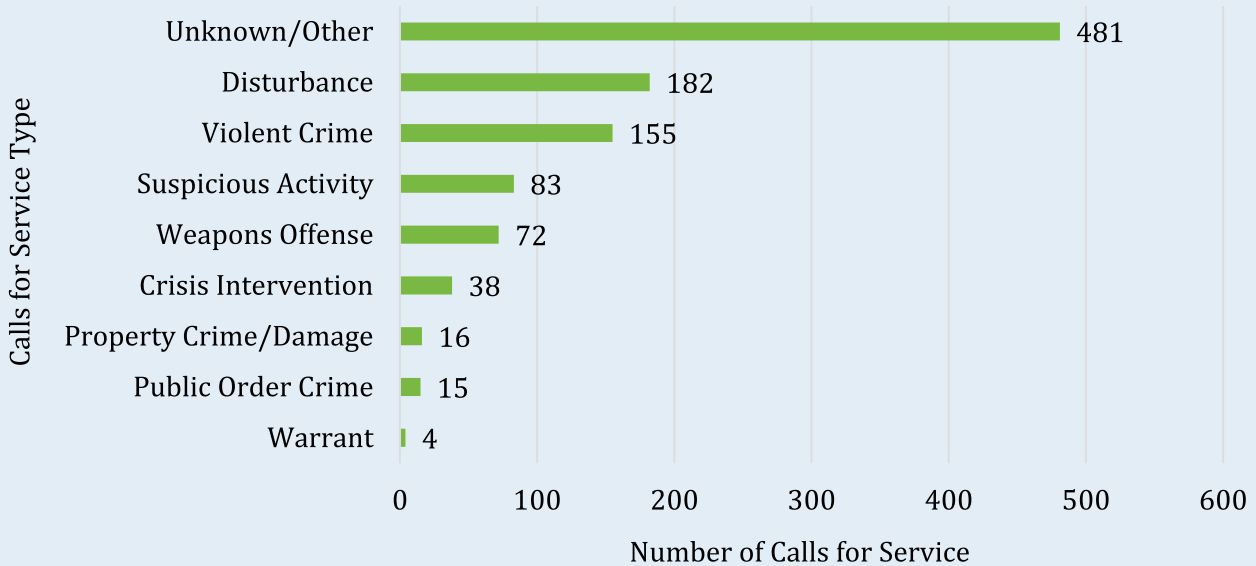
Source: Calls for service data provided by Spokane (WA) Police Department.

Houston Police Department, Texas

The Houston Police Department (HPD) is the main public safety entity for the City of Houston, Texas. Houston is the highest populated city in Texas, with an estimated population of 2,304,580.[11] Based on the calls for service analyzed, officer injuries on calls for service in the HPD are rare. Of 3,059,851 calls for service from 2015 to 2018,[12] only 1,046 (0.03 percent) resulted in an officer injury. We also analyzed calls for service in which a suspect resisted arrest (13,556 calls for service) or possessed a weapon (2,282 calls for service).

Figure 4 displays the number of calls for service that resulted in officer injuries between 2015 and 2018. Between 2015 and 2018, unknown/other calls for service accounted for 481 total calls for service resulting in officer injuries (50 percent), with disturbances accounting for 182 calls for service (17.3 percent).

Figure 4. Calls for service resulting in officer injuries in Houston Police Department, Texas: 2015–2018



Source: Calls for service data provided by Houston (TX) Police Department.

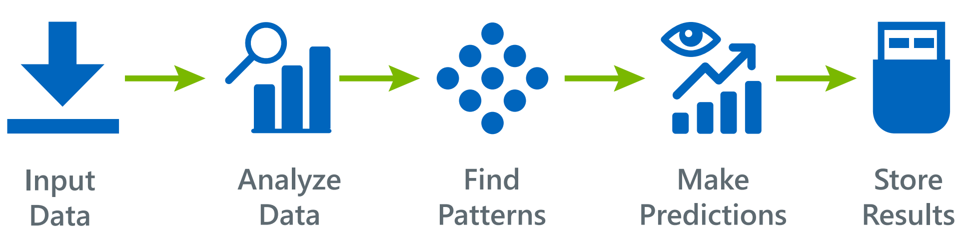
SECTION 2
DEVELOPMENT OF PILOT RISK ASSESSMENT MODELS

Using machine learning techniques, we developed models to forecast risk and identify influential drivers of threat to officer injury. We used machine learning models because they (1) are well suited for the complex nature of criminological data,[13] (2) have the ability to identify patterns and relationships in large datasets,[14] (3) have greater forecasting accuracy than more conventional models,[15] and (4) are able to forecast rare events and incorporate agencies' tolerance for different kinds of risk. In this section, we provide an overview of machine learning, discuss potential vulnerabilities in developing and using machine learning, discuss how we used this predictive technique to develop agency-specific pilot risk assessment models, and summarize the overall ability of the developed models to forecast risk and threats to officer injury. We provide the results of the agency-specific pilot risk assessment models in Section 3.

OVERVIEW OF MACHINE LEARNING

The goal of **machine learning** is "to develop methods that can automatically detect patterns in data, and then to use the uncovered patterns to predict future data or other outcomes of interest."[16] Figure 5 shows the basic steps of the machine learning process. In the context of policing, past calls for service data are analyzed using a machine learning model to detect patterns and relationships. Then these patterns are used to make predictions about the outcomes of the calls for service.

Figure 5. Machine learning process



Source: CNA.

Machine learning can overcome several limitations of conventional predictive analytics. One limitation is that the conventional regression model cannot effectively incorporate costs into the model.[17] *Cost* in this sense refers to the consequences of making incorrect predictions—that is, the false positives or false negatives that can result from the predictive analysis. Berk and Bleich (2013) stress that the consequences or weight of false negatives and false positives are not the same and that costs should be incorporated into predictive models.[18] For example, as described in Berk and Bleich (2013), when forecasting parole success for individuals, the cost of paroling an individual who will fail and may commit a serious crime is not equal to the cost of denying parole for an individual who will succeed. Some stakeholders may view the former as more costly, while other stakeholders may view the latter as more costly. Both situations involve costs, but they are not the same.

The use of machine learning and other statistical approaches sometimes raises concerns about potential bias. Recognizing the potential for bias is important. While these biases can sometimes stem from assumptions made in the modeling process, biases in the underlying data are usually the principal cause for concern. Readers should be aware that biases in reporting and collecting officer injuries, as well as in how officers respond to different kinds of calls for service, will be mirrored in the model and its risk assessments. While we have gone to great lengths to build the model using objective interpretations of how events transpired, these biases could sometimes lead the model to identify a situation as high risk when in fact that situation reflects low risk to officers. Concerns about the potential for bias in machine learning are important to evaluate, and these techniques offer opportunities for objective empirical examination of divisive topics to minimize the bias that is already present in the real world.

APPLICATION OF MACHINE LEARNING TO CALLS FOR SERVICE DATA

The application of machine learning to calls for service data warranted three primary decisions: (1) how to define *high risk*, (2) the costs associated with officer injuries, and (3) the type of machine learning model to use.

> *In addition to calls for service in which an officer was injured, we included calls for service in which the suspect(s) eluded or resisted arrest and calls for service in which the suspect(s) possessed a weapon as high-risk incidents.*

1. DEFINING HIGH RISK

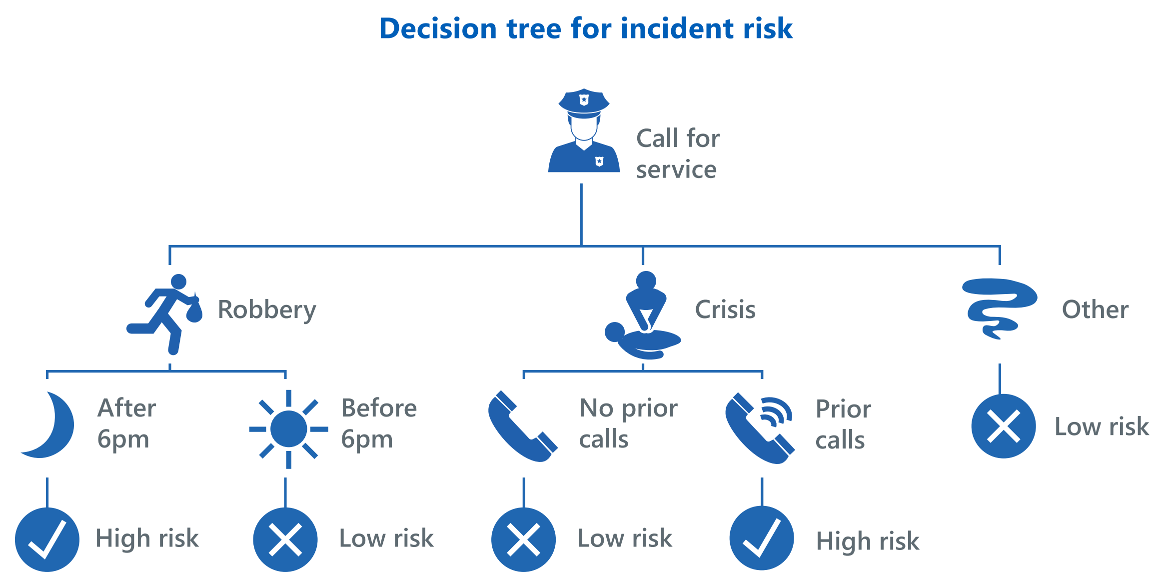
In addition to predicting incidents in which an officer was injured, we decided to include whether the suspect(s) eluded or resisted arrest and whether the suspect possessed a weapon, since both situations pose significant risk to officers. We decided to classify incidents in which suspects eluded or resisted arrest as high risk because many of the injuries observed in the LEOKA data provided by agencies resulted from officers chasing suspects who were eluding arrest or engaging with suspects who were resisting arrest. Similarly, we classified incidents in which the suspect possessed a weapon[19] as high risk because injuries sustained by officers during these incidents were more likely to be serious. We made these inclusion decisions because many of the factors leading to officer injuries are highly idiosyncratic and depend on how incidents transpire after officers arrive on the scene. Some information is not available to dispatch and thus cannot be incorporated into a forecasting model (e.g., information about an officer's ability to de-escalate an incident that might otherwise have led to an injury). Further, our Advisory Group members[20] and project agencies posed the concern that officers might receive injuries but choose not to report them, which suggests that data on injuries might be incomplete. Incidents that pose a high risk to officer safety (e.g., presence of a weapon), however, may be easier to identify based on the information available at dispatch and less likely to suffer reporting bias.

2. COST RATIO

Advisory Group members and project agencies stressed that not being prepared for a high-risk situation (e.g., approaching a hostile suspect alone) is worse for an officer than being over-prepared (e.g., waiting for backup units). As a result, we built a model that weighted the cost of false negatives (predicting that an officer is NOT entering a high-risk situation when they are) five times greater than false positives (predicting that an officer is entering a high-risk situation when they are NOT). We chose a ratio of 5:1 to represent the idea that these kinds of errors are substantively more costly to agencies but not overwhelmingly (e.g., 10:1 or 100:1). Determining exactly what this ratio should be is an art rather than a science, and so these numbers can vary. Ideally, agencies would be involved in setting the weight assigned to false positive and false negatives.

Figure 6. Decision tree process

Rather than assuming a continuous relationship, a decision tree splits the data at various cut points.



Source: CNA.

3. MACHINE LEARNING MODEL

After considering the range of machine learning models available, we implemented a gradient boosting model, which is a type of ensemble decision tree (Figure 6). One general advantage of the decision tree approach is that it naturally builds in complicated interactions between the variables that would have to be manually specified in a linear regression. Although models built with a single decision tree often perform poorly on new, unseen data, machine learning models that iteratively combine many smaller decision trees tend to perform much better. The term *ensemble* refers to this process of combining many smaller models into a single larger model. The types of models generally perform better than a single larger model, but at a cost to interpretability because the results reflect the output of many trees, not a single tree.

Among the many types of ensemble decision tree models, we chose gradient boosting because it outputs probabilities for forecasted outcomes and showed strong performance in an initial validation test. We also considered simple logistic regression, logistic regression with a LASSO (least absolute shrinkage and selection operator) regularization term, random forest, and neural net models.

Three ways to measure model performance:

1. ***Accuracy:*** *the fraction of correct predictions*
2. ***Recall:*** *the fraction of correctly identified cases*
3. ***Precision:*** *the fraction of positive classifications*

We implemented gradient boosting using the generalized boosted models (gbm) library in R (a free programming language and software package) and adjusted many of the default settings to fit our instance of extreme class imbalance. For each agency, we iteratively increased the weight assigned to high-risk situations until performance statistics showed about five times more false positives than false negatives. We chose this ratio because it reflected the higher cost with missing a potential high-risk situation. To maximize performance, we generated many decision trees (1,000) and then selected the best number of trees using a random sample of the data that was withheld at each stage of fitting the model.

We emphasize that these models identify the percentages of time that factors *correlate* with officer injuries, not the factors that *cause* officer injuries. Notably, without the randomized assignment that would be applied during an experiment, associations between officer injuries and related factors would be open to selection bias. For example, officers and agencies have beliefs about which kinds of calls for service are the most dangerous to officers and will make decisions about how to approach these calls based on those beliefs. Agencies will therefore be more likely to send multiple officers to calls that are believed to pose a higher risk, and officers are more likely to prepare for risk mitigation. Because of these anticipatory actions, the observed injuries resulting from these incidents will be lower than would have been observed otherwise. The models do allow us to identify which calls for service are the most likely to lead to officer injuries. Although not causal, this predictive estimate is still important for agencies because it can help decide how to change policies and resource allocations to reduce risk.

While the model's forecasting accuracy is important when evaluating whether such a tool could be useful in the field, we are also interested in understanding the factors that contribute to these predictions. Machine learning models are sometimes characterized as "black boxes" with little insight into their inner workings. This may have been true when these methods were in their infancy, but there have been significant advances in model interpretation that help demonstrate the factors that are contributing to a model's predictions.

SECTION 3
AGGREGATE PILOT RISK ASSESSMENT MODEL RESULTS

For each agency, we fit a machine learning model using the process described in Section 2. Because the circumstances faced by each agency differ, the model's predictive accuracy and the specific weight assigned to each risk factor vary from agency to agency. This section describes the overall results that we can infer from analyzing these models together. Agency-specific results can be found in Appendix A. When considered as a whole, the analysis demonstrates that the machine learning models have the potential to produce risk assessment models to identify high-risk incidents and threats that may cause officer injury. The models developed by this project can identify a significant fraction (37 percent) of the high-risk situations, but at the cost of significant false alarms (88 percent). These shortcomings come primarily from the limited information available to the model. While the pilot risk assessment model is likely not strong enough to deploy in the field today, further collaboration with agencies, patrol officers, and dispatch could identify additional data that would improve the model's predictions. In this section, we detail the criteria we used to evaluate whether the machine learning models produced a viable model, and then we summarize the model results. Finally, it is important to keep in mind that the risks we observe to officer injuries depend on current policies, procedures, context, and approaches. The model will reflect the differences in how agencies and officers respond to calls for service. To the extent that officers are systematically better at deescalating certain calls for service, the model will reflect these differences in outcomes.

ASSESSING THE MODEL'S PREDICTIONS

As is standard practice, we split our data into three segments: a validation dataset (20 percent) on which to tune model parameters, a training dataset (60 percent) on which to build the model, and a testing dataset (20 percent) on which to evaluate the model's performance. After building the risk model based on the training set and tuning the model with the validation set, we evaluated the model using the testing set, which is data that the model had not seen before. By evaluating the model on a separate sample that was not used to generate the model parameters, we gain a more reliable sense of how the model would perform in the real world.

In predicting whether a call for service met any of our three criteria for a high-risk incident, our model accurately classified 98 percent of the unseen calls for service in the training set. Although this accuracy measure is impressive, this result is strongly influenced by the rarity of officer injuries. Since injuries are so rare, if we predicted that all calls for service resulted in no injury, we would accurately predict 99 percent of all cases. This "no injury" model would, in a technical sense, be more accurate than our model, but it would not help agencies discriminate between calls for service and would not be useful.

The goal for our pilot risk assessment model is not to accurately classify the largest number of cases but to identify the small number of injuries that occur while also minimizing the number of low-risk incidents that are incorrectly identified as high risk. This first measure (i.e., how many officer injuries were identified correctly by the model) is known as *recall* and can be thought of as how many needles in a haystack can be recovered. In this case, our model identified 849 of 2,316 high-risk incidents in the testing set, so it had a recall of about 37 percent. For every high-risk incident, the model was able to flag these cases based only on the information available to dispatch approximately one third of the time.

In machine learning, we divide the data into three segments:

1. ***Training Set:*** *generate the model estimates*
2. ***Validation Set:*** *tune model for best performance*
3. ***Testing Set:*** *evaluate the model's performance*

Identifying these injuries, however, comes at the cost of flagging low-risk incidents as high risk, a metric known as *precision*. Our model flagged 6,986 calls for service as potentially high risk, of which only 849 were actually high-risk incidents, a precision of 12 percent. This means that when the model predicted that a call for service was high risk, this prediction was correct about one out of every ten times. The model therefore performs less well on precision than it does on recall. One of the reasons why the model generates so many false positives is that we programmed it to err on the side of caution—to overidentify false positives and under identify false negatives. If agencies determined that this rate of false positives was too high, they could adjust the model to assign less preference to the positive cases, but in doing so would decrease the model's recall. Agencies might decide that this risk of false positives was too high if they were concerned about officers being hypervigilant and escalating situations that might otherwise be low risk. Addressing those concerns requires calibrating the model to an agency's particular set of concerns.

Table 1. Model accuracy, precision, and recall

Predicted Outcome	Actual Outcome: Low-risk	Actual Outcome: High-risk
Low-risk	313,472	1,467
High-risk	6,137	849

Source: Law Enforcement Officers Killed and Assaulted (LEOKA) officer injury data.

The recall and precision of this pilot model are likely not strong enough for agencies to deploy in the field as is, but the results demonstrate that the machine learning models can detect important patterns in the data. Despite representing less than 1 percent of the total calls for service, the model can identify about a third of the high-risk situations based only on information about enabling conditions. Capturing additional call for service-specific information into the model would further improve its predictive accuracy and would require additional partnership with agencies to flag these pieces of data at dispatch.

INTERPRETING THE MODEL'S PREDICTIONS

Beyond generating predictions for specific calls for service, the model results can also help us understand the factors contributing to high-risk incidents. As introduced in Section 1, the model drew from 81 different variables to generate its predictions. Across the four project agencies, call for service type proved to be the most important factor in predicting a high-risk incident. Call for service type refers to the nature of the problem generating the call for service, such as domestic abuse, assault, noise complaints, or drug use. In three of the four agencies, the time of day was the second most important factor contributing to the model's predictions but was not nearly as important as the incident type. Other factors such as previous calls to the same location, local area trends, weather, and census tract details did not help distinguish between calls for service. Table 2 below ranks the top five factors contributing to each agency's risk model. Color density represents the strength of the variable's contribution to the predictions. Factors below the top three were generally insignificant and could not be distinguished based on importance. We assessed each variable's contribution to the models predictions using permutation importance.[21]

Table 2. Factors contributing to the model's risk scores

	Agency 1	Agency 2	Agency 3	Agency 4
1	Call for service type	Call for service type	Call for service type	Call for service type
2	Time of day	Location details	Time of day	Time of day
3	Year	Location details	Month	Location details
4	Month	Time of day	District trends	Month
5	Location details	District trends	District trends	Agency trends

Source: CNA.

Repeated variables represent different transformations of similar information. Specific strengths and transformations can be found in Appendix A.

The finding that the call for service type and the time of day contribute the most to understanding whether officers are at risk tells us that agencies need not invest in updating information systems. Incorporating additional factors such as weather or location trends adds little additional predictive power. However, further work is needed with agencies to identify additional information that could be known at dispatch that could be incorporated into a risk assessment model to improve its predictive accuracy over our baseline estimates.

Of further interest, the model finds that census tract details, such as vacancy rates, employment, and racial demographics, contribute very little to understanding risks to officer safety. These factors may consciously or unconsciously shape how officers think about the risks associated with calls for service in different neighborhoods. An evidence-based policing approach, however, would suggest that these factors should not be considered when evaluating risk and that agencies should focus on the nature of the call for service and time of day.

CALLS FOR SERVICE TYPES MOST ASSOCIATED WITH RISK

The variable importance metrics indicate that type of call is the single most important factor contributing to the risk associated with a call for service. These same models can also help us understand which types of incidents are associated with the greatest risk. To understand the risk posed by specific call types, we constructed partial dependence plots which reflect the average risk score if all calls for service were from that particular type. By measuring risk in this way, we keep all other characteristics of these calls for service the same and capture their contribution to the risk scores.[22] Table 3 below summarizes the results of these partial dependence plots and shows the top ten incident types for each agency.

Looking across agencies, we find that calls for service associated with shots fired or firearm observed, robberies, and assaults were the most likely to result in risk to officer safety. Calls for service involving weapons are mechanically associated with risks to officer safety because this is one of the criteria we use to judge whether officers are at risk. This general finding did not hold for Agency 4, where calls related to drugs violations, missing persons, and crisis interventions ranked more highly than those involving weapons. This may reflect differences in how agencies report other aspects of officer risk, such as whether suspects resisted arrest, or how they categorized incident types.

Table 3. Risk associated with particular call for service types

	Agency 1	Agency 2	Agency 3	Agency 4
1	Shots/Firearm	Robbery	Weapons Offense	Drugs Violation
2	Robbery	Weapons Offense	Shots/Firearm	Missing Person
3	Assault	Shots/Firearm	Warrant	Crisis Intervention
4	Weapons Offense	Assault	Drugs Violation	Weapons Offense
5	Child Abuse	Sexual Assault	Assault	Warrant
6	Warrant	Domestic Violence	Domestic Violence	Shots/Firearm
7	Domestic Violence	Warrant	Robbery	Assault
8	Sexual Assault	Alcohol	Suspicious Activity	Other Services
9	Suspicious Activity	Homicide	Burglary	Homicide
10	Alcohol	Disturbance	Disturbance	Sexual Assault

Source: Calls for service data provided by participating agencies and LEOKA injury data.

Color density represents the call for service type's contribution to the predicted risk. Specific values can be found in Appendix A.

Of particular interest, the personnel surveys, summarized in Section 4, indicated that patrol officers felt the call for service that poses the greatest risk to officer safety was domestic violence, followed by shooting in progress and behavioral/mental health crisis. However, according to the risk assessment models, domestic violence calls were typically about the sixth or seventh most dangerous type of call. This empirical analysis allows us to evaluate the risks that officers face and to consider the effectiveness of policies put in place by agencies to reduce the risk of injury associated with certain calls for service. If agencies and officers respond more cautiously to domestic violence calls, then these efforts will be reflected in the lower risk assessments. Further data on how agencies respond to specific calls for service would help the model control for differences in responses and evaluate the inherent risk of these incidents.

SECTION 4
OFFICER PERSPECTIVES ON TRAINING, RISK, AND DISPATCH

In July and August 2021, we collected data on the following:

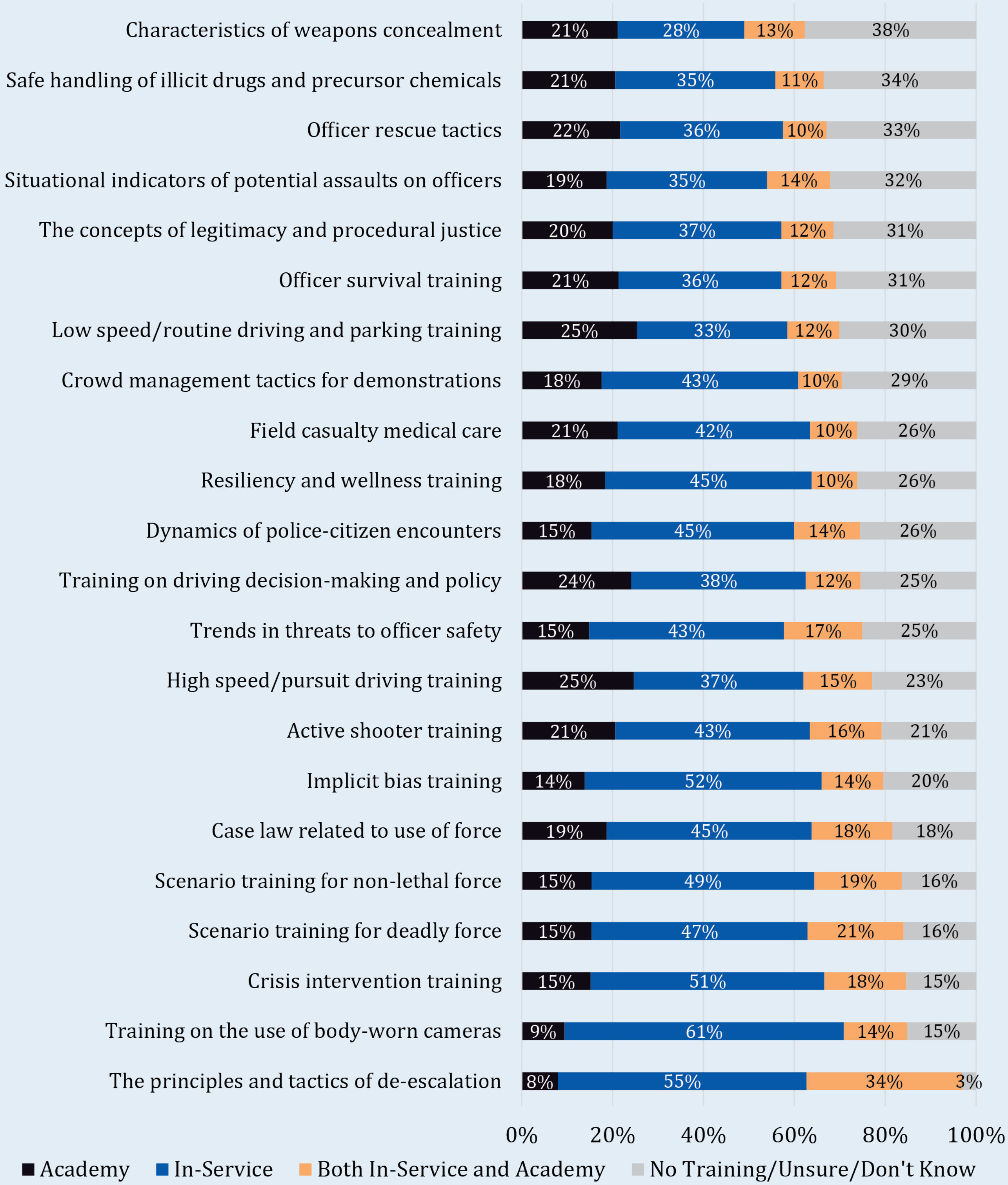
- **Perceptions of risk** to patrol officer safety
- How patrol officers actively **protect themselves from the risks** associated with responding to calls for service
- How patrol officers and dispatch personnel **work together to mitigate risk**
- How patrol officers **train on officer safety**
- The ways in which agencies can **improve patrol officer safety**

We conducted virtual interviews covering these topics with a total of 10 command staff and 7 patrol officers from the CCPD, CPD, HPD, and SPD. We also administered online surveys to patrol officers or those who had served on patrol within the last year at each of the agencies, resulting in responses from 608 officers across project agencies. In this section, we summarize aggregated survey and interview results across all project agencies on training, risk and response, and information received from dispatch.

TRAINING

The officers in each agency indicated the trainings they had received over the last three years, detailed in Figure 7. Responses indicated that most officers participated in 23 of the listed trainings within the last three years. However, only 50 percent of respondents indicated that they received some sort of training on recognizing and countering ambush attacks. The most frequently attended trainings were on de-escalation, with roughly 97 percent of officers attending. Approximately 85 percent of respondents stated that they were trained on body-worn cameras, crisis intervention, scenario training for use of deadly force, and scenario training for use of nonlethal force. Officers interviewed also indicated the many methods of training employed to enhance officer safety, such as roll-call training, scenario-based training, virtual reality, hands-on training, and field training.

Figure 7. Training received in the past three years



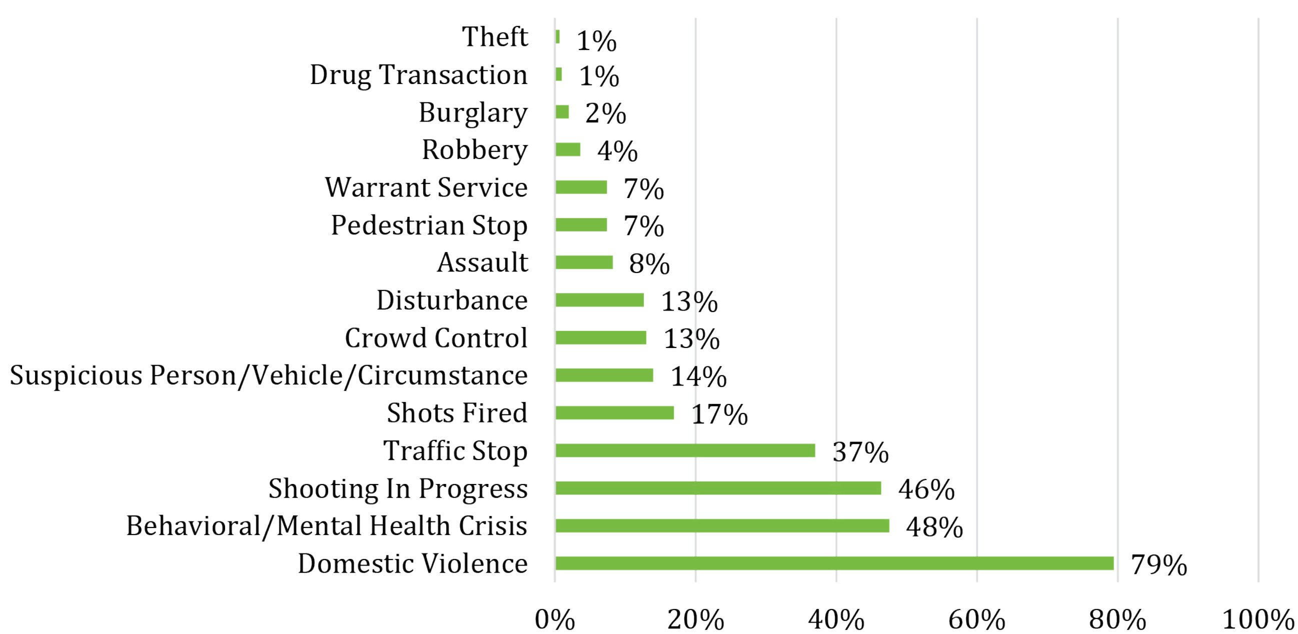
Source: CNA Officer Safety Survey administered to participating agencies.

Officers noted that the topics covered in trainings pertaining to officer safety included but were not limited to firearms, pistol qualifications, defensive tactics, tactical driving, and use of force. One officer mentioned they felt the newer officers would be safer if they were more confident and better able to regulate their emotions. This officer recommended mindfulness training to make sure people can regulate their emotions in times of stress and to ensure the agency deploys more confident officers who can de-escalate situations with patience. Multiple officers also recommended that officers become more proficient with hands-on control like Jiu Jitsu or other control tactics.

RISK AND RESPONSE

Officers were asked to identify the top three calls for service or self-initiated call types that they considered pose the greatest risk to officer safety. Respondents were provided a list of 16 common activities officers experience during their work (Figure 8). Of all the call types, the vast majority of officers (79 percent) included domestic violence situations within the top three highest risk events, followed by individuals in a behavioral/mental health crisis (48 percent) and notifications of a shooting in progress (46 percent). During the virtual interviews, officers expressed that the risk associated with domestic disturbances was high because of the strong emotions typically present during the encounters, the officer's unfamiliarity with the layout of the location, and the high likelihood of an arrest occurring. Notably, in each agency-specific section above, the model predicted a different level of risk than the interviewed and surveyed officers. Officers were shown to disproportionately assign risk to domestic disturbance/violence calls.

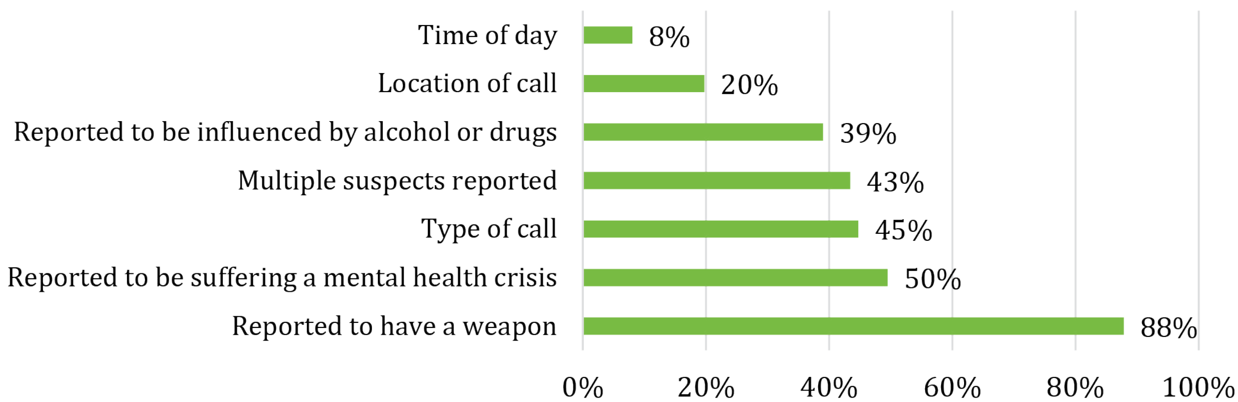
Figure 8. Officer perceptions of the risk level of the 16 types of common calls for service or self-initiated calls



Source: CNA Officer Safety Survey administered to participating agencies.

Figure 9 details the officers' perspectives on the factors considered important in determining the risk level prior to arriving at a call for service, including the top three factors. Officers learn much of this information through the call notes or through the dispatcher, although some information comes more informally through radio conversation between officers. The leading factor, which 88 percent of officers reported as an important factor, was whether the individual is reported to have a weapon. The second leading factor was whether the individual is reported to be experiencing a mental health crisis.

Figure 9. Factors considered to be the most important in determining the risk level of a call prior to arriving

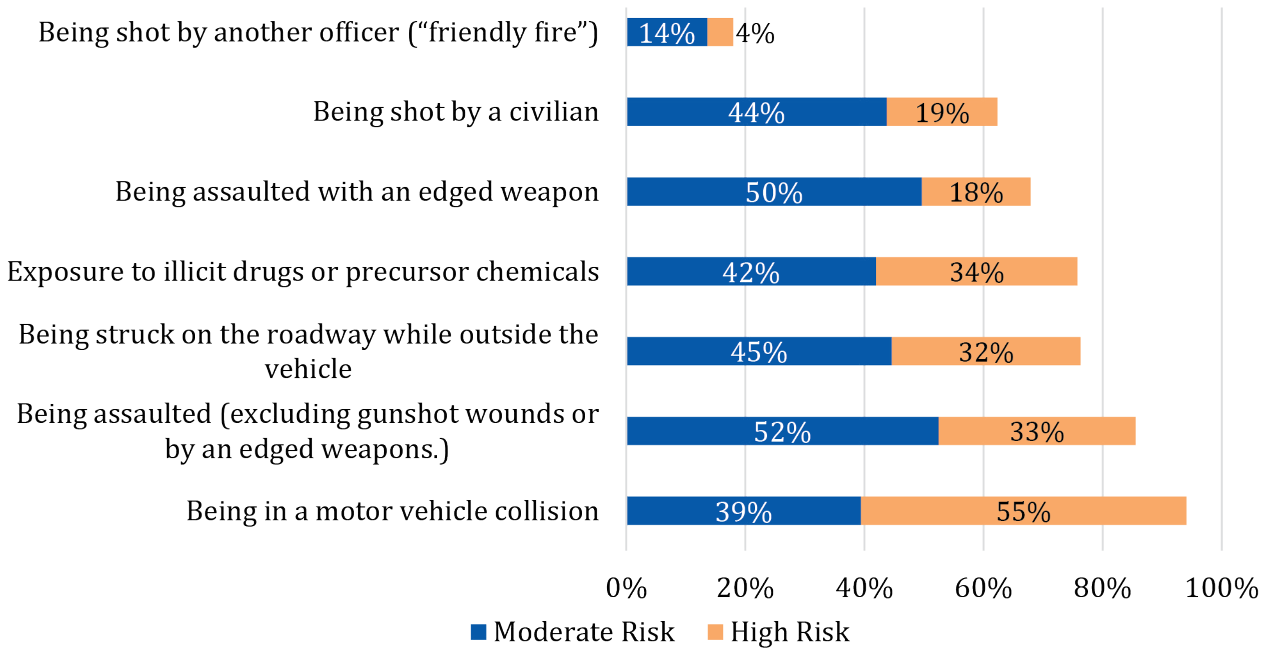


Source: CNA Officer Safety Survey administered to participating agencies.

Officers were asked to rate the potential risk to officers in their department being seriously injured across seven volatile events, such as being shot by another officer, being shot by a civilian, or being in a motor vehicle collision. Responses included "low," "moderate," and "high." Figure 10 details the percent of officers who rated an event as a moderate or high risk for officer injury.

The leading rated event for potential injury was officers being involved in a motor vehicle collision, which 55 percent of officers rated as high risk and 39 percent rated as moderate risk. Being exposed to illicit drugs, assaulted, or struck on a roadway by a vehicle were each rated as high risk by approximately 33 percent of officers. Roughly 52 percent of officers viewed being assaulted as a moderate risk as well, making it the second riskiest type of event overall. Although officers may view these events as having a high potential for injury, approximately 69 percent of officers advised that they felt their department provided them with the equipment needed to ensure their physical safety when responding to and initiating calls for service.

Figure 10. Percentage of "moderate" and "high" responses on the potential risk of officers being seriously injured by the following events

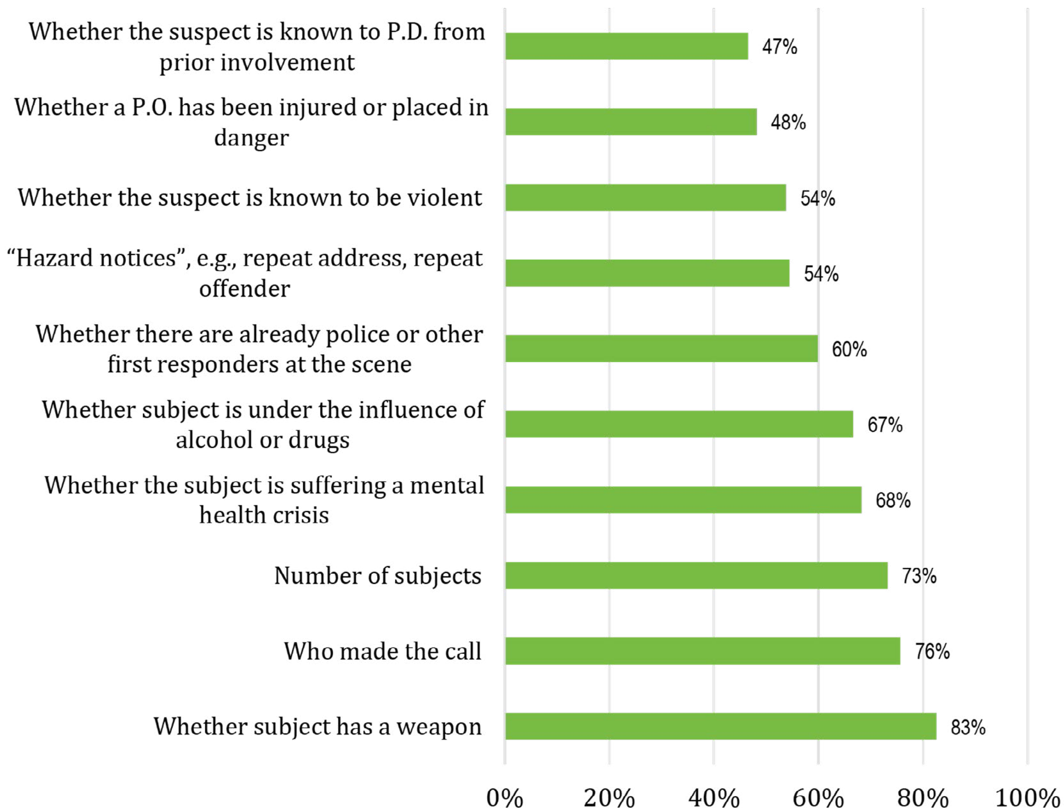


Source: CNA Officer Safety Survey administered to participating agencies.

DISPATCH

Through the work associated with this project, the team identified the critical role of call-takers and dispatch personnel in officer safety. Notably, officers in participating agencies differentiated the two types of personnel, had varying levels of trust in them, and had separate relationships with the call-takers and the dispatchers who provide information to them. (However, this varies by agency because call-takers and dispatchers are not uniform functions across agencies nationwide.[23]) For example, officers mentioned they felt that call-takers do not ask the correct questions or follow-ups and are often rushed to get through a script in a certain amount of time, and that information is lost in the transition from call-taker to dispatcher to officer. With regard to dispatch, officers mentioned that dispatchers will check in with officers while they are on the scene, and will call for backup if the officer does not verbally respond to dispatch within a certain timeframe. Dispatchers also provide critical information prior to the officer arriving at the scene, with 37 percent of officers reporting that they received good information from dispatch. Only 11 percent of officers rated the quality of information from dispatch as poor or very poor. Figure 11 details the kind of information that is typically available to officers from dispatch when responding to a call for service. Eight out of ten officers reported that dispatch informs officers whether the subject has a weapon, while roughly 70 percent of officers reported that they receive information on who made the call, the number of subjects, and whether the subject appears to be under the influence of drugs or alcohol or experiencing a mental health crisis.

Figure 11. Information that is typically available to officers from dispatch when responding to a call for service



Source: CNA Officer Safety Survey administered to participating agencies.

Additional information, such as whether the suspect has a history with the department or is known to be violent, sometimes depends on the caller's willingness to convey additional knowledge to the dispatcher, and sometimes comes down to a dispatcher's skill. Interviewed officers advised that some dispatchers feed additional information on the suspects, victims, and address to the officer while they are responding; however, interviewed officers felt that much of that work correlates with the dispatcher's experience on the job. Officers highlighted additional information that helps their response to calls for service including real-time updates, suspect or caller history, address history, whether weapons are registered at the address, known threats to police, and specific information related to domestic violence calls. Other helpful information includes repeating what the subject is doing and wearing, whether the subject is still at the location or what direction they went, the number of parties present, and a time lapse of when the event occurred (e.g., whether 5 minutes ago or 5 hours ago).

Clear and accurate call type labels were also deemed important by officers. One officer stated that a misclassification of a call type, such as a domestic disturbance or mental/behavioral health crisis, can lead to one officer being present at a two-officer recommended call, which increases the risk to the responding officer. Another officer expressed frustration about receiving inaccurate information and fears of wrongly detaining an individual.

SECTION 5
RECOMMENDATIONS

Officer safety is a central concern of all law enforcement operations, and agencies can implement specific measures to enhance the safety of their officers. Based on our research, data analysis, interviews, and survey results, we compiled a list of recommendations to improve officer safety. The recommendations are organized into five categories: data, risk and response, training, dispatch, and equipment.

DATA

- Departments should **collect robust injury-related data** (e.g., dispatch characteristics, response characteristics, officer tactics, injury severity) to better forecast risks, inform training, evaluate risk mitigation strategies, and revise policies, procedures, and practices. More information on this topic is available in the Guidance on the Collection and Use of Officer Injury Data Bulletin.
- Departments should **provide annual data** to their employees on officer assaults to show the actual risk officers face and incorporate a data-driven approach into the agency.
- Departments should **engage officers regularly for their feedback** regarding safety so the department may adequately address the concerns of their staff.

RISK AND RESPONSE

- Departments should engage line-level officers to **examine why officers may be reluctant to report injuries**, minor or major, and address these hesitancies.
- To ensure adequate coverage to respond to all calls for service, agencies with limited staff should consider **creating local or state partnerships** with neighboring agencies to increase the number of officers available for dispatch.

TRAINING

- Departments should provide **scenario-based training** on a consistent basis that allows officers to evaluate and assess risk they are likely to encounter in the real world.
- Departments should conduct an **internal analysis of the most common types of assaults** on officers and implement training and other mitigations of the risks associated with these types of assaults.
- Departments should train all officers on radio communication and find ways to **incorporate radio communication in trainings** to more effectively relay important information to officers when responding to calls for service.
- Departments should ensure their f**ield training officers (FTO) are exhibiting appropriate officer safety behavior** and ensure the FTO program has adequate supervision to monitor and address negative officer safety behavior in trainees or FTOs.

DISPATCH

- Departments should foster effective and **quality relationship building** between dispatch and patrol through regular meetings.
- Departments should offer **co-training opportunities** between patrol officers and dispatch personnel that center around clear and concise communication methods, information probes (call type specific), and updated call details.
- Departments should encourage dispatchers and call takers to go on **ride alongs** with officers and grant officers time to **sit in with call takers** and dispatchers.
- Departments should **review dispatch policy and protocols** periodically to determine what information can be added to calls for service (e.g., new databases, information shared from other agencies, “flags” of a person or place).
- **Dispatch and call taker scripts** should continually be evaluated based on the needs of patrol officers and the community.[24]
- Departments should work with dispatchers and call takers to **create checklists and collect descriptions of off-duty, plainclothes, and undercover officers on the scene**. Similarly, there should be clear protocols set for officers in plainclothes to inform the dispatcher if they are responding and armed.

EQUIPMENT

- Departments should provide **supplemental training with equipment** relating to officer safety to help with muscle memory in stressful situations.
- Departments should use their **incident report data to review call type** and equipment used during incidents to determine whether appropriate equipment is being used when responding to calls for service.
- Departments should consider applying to the **Edward Byrne Memorial Justice Assistance Grant**[25] and the **Patrick Leahy Bulletproof Vest Partnership**[26] to fund equipment.
- To adjust to ongoing legislation, departments should hold ongoing discussions with officers to ensure they are **up to date on policy and training for equipment and responses** that are allowed and discuss risk mitigation measures for any officer concerns.

CONCLUSION

The primary goal of the **Using Analytics to Improve Officer Safety** project is to support efforts to improve officer safety in the field. Thus far, we have approached this goal in several ways. First, we explored whether machine learning could identify high-risk incidents to officers in four police agencies. The ability of a model to flag high-risk incidents prior to officers arriving on scene would be of critical importance to an officer's ability to take appropriate risk mitigation actions. To build such a model, we used calls for service and LEOKA data from each of the four agencies. Overall, the machine learning model correctly identified officer injuries about half of the time in the participating agencies. Given the rarity of officer injuries within the four agencies, being able to identify half of such rare situations is noteworthy. In addition, the model was able to identify the factors that were the most important in forecasting risk to officer safety, and the types of calls of service that posed the highest risk to officer safety. Our work demonstrates that such machine learning has the potential to forecast officer injuries; whether such a model could be built into the dispatch process should be explored so officers would be informed about potential risk factors before arriving at a call. The model also highlighted factors and call for service types that pose greater risks to officer safety. The results of the machine learning model, along with the results from the officer interviews and surveys, also highlighted an often-overlooked entity in police operations that is critically important to officer safety: dispatch.

We hope that by providing participating agencies with a foundational knowledge of risks to officer safety, they will have a basis for modifications to policy, training, and operations, leading to the implementation of strategies, processes, and procedures to keep officers and the communities they serve safe.

Below we highlight two avenues of research for the field to further explore risk and promote officer safety.

EXAMINE THE RISK OF OFFICER INJURY DURING TRAFFIC STOPS: Although the issue of felonious assaults against officers deserves serious attention, reducing traffic-related injuries and fatalities among officers is equally important. Motor vehicle–related incidents, including being struck by a vehicle or involved in a crash, have been one of the leading causes of line-of-duty deaths for officers.[27] Risk factors associated with officer injuries during traffic stops stand apart from those related to other calls for service types.

EXPLORE THE ROLE OF DISPATCH: Increased and more effective communication between officers and dispatch personnel has been identified as a key practice to reduce risks to officer safety.[28] By sharing clear and relevant information, dispatch personnel can lower the risk to officers, especially when officers respond from different jurisdictions or may not have access to all pertinent information (e.g., call information, history of the location, history of location occupants).

APPENDIX A
AGENCY-SPECIFIC RESULTS

CONFUSION MATRIX

Table A.1: Model predictions and actuals for Camden Police Department, New Jersey

		Actual		
		Low Risk	High Risk	TOTAL
Predicted	Low Risk	71,145 (TN)	574 (FN)	71,719
	High Risk	1,978 (FP)	393 (TP)	2,371
	TOTAL	73,123	967	74,090

Source: Calls for service data provided by Camden County (NJ) Police Department and LEOKA officer injury data.

Note: Confusion matrix for model results from the Camden Police Department. True Negative (TN), False Negative (FN), False Positive (FP), True Positive (TP).

Table A.2: Model predictions and actuals for Columbia Police Department, South Carolina

		Actual		
		Low Risk	High Risk	TOTAL
Predicted	Low Risk	118,053 (TN)	345 (FN)	118,398
	High Risk	2,319 (FP)	377 (TP)	2,696
	TOTAL	120,372	722	121,094

Source: Calls for service data provided by Columbia (SC) Police Department and LEOKA officer injury data.

Note: Confusion matrix for model results from the City of Columbia Police Department. True Negative (TN), False Negative (FN), False Positive (FP), True Positive (TP).

Table A.3: Model predictions and actuals for Spokane Police Department, Washington

		Actual		
		Low Risk	High Risk	TOTAL
Predicted	Low Risk	21,314(TN)	142 (FN)	21,456
	High Risk	652 (FP)	30 (TP)	682
	TOTAL	21,966	172	22,138

Source: Calls for service data provided by Spokane (WA) Police Department and LEOKA officer injury data.

Note: Confusion matrix for model results from the Spokane Police Department. True Negative (TN), False Negative (FN), False Positive (FP), True Positive (TP).

Table A.4: Model predictions and actuals for Houston Police Department, Texas

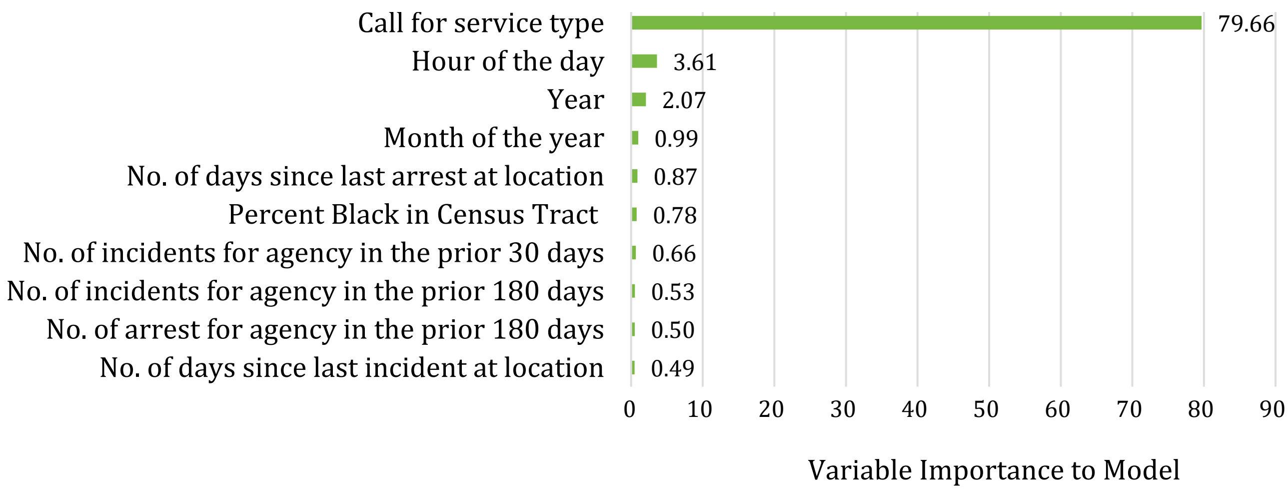
		Actual		
		Low Risk	High Risk	TOTAL
Predicted	Low Risk	102,960 (TN)	406 (FN)	103,366
	High Risk	1,188 (FP)	49 (TP)	1,237
	TOTAL	104,148	455	104,603

Source: Calls for service data provided by Houston (TX) Police Department and LEOKA officer injury data.

Note: Confusion matrix for model results from the Houston Police Department. True Negative (TN), False Negative (FN), False Positive (FP), True Positive (TP).

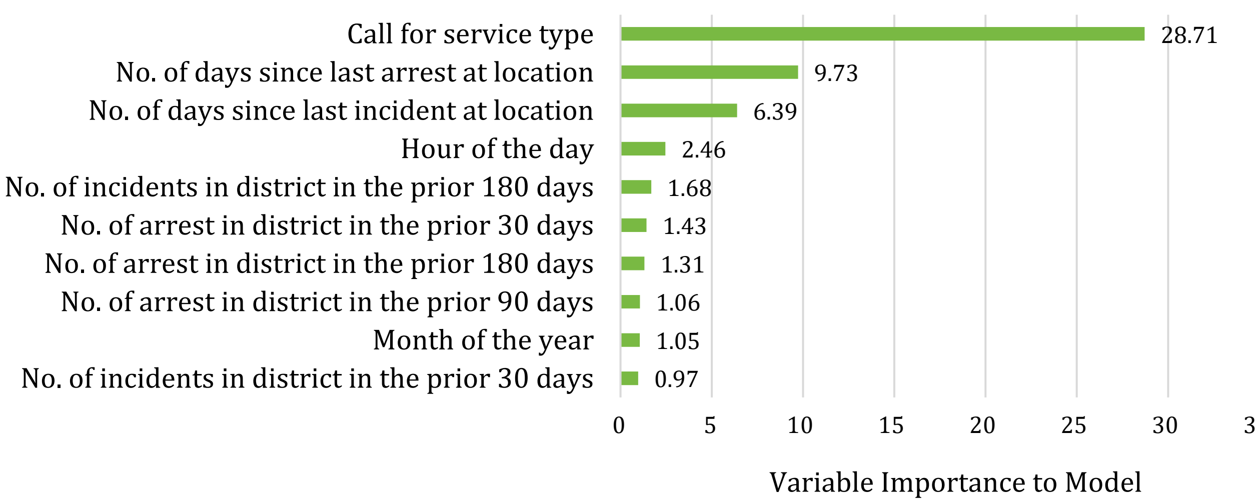
VARIABLE IMPORTANCE

Figure A.1: Top 10 variables supporting model for Camden County Police Department, New Jersey



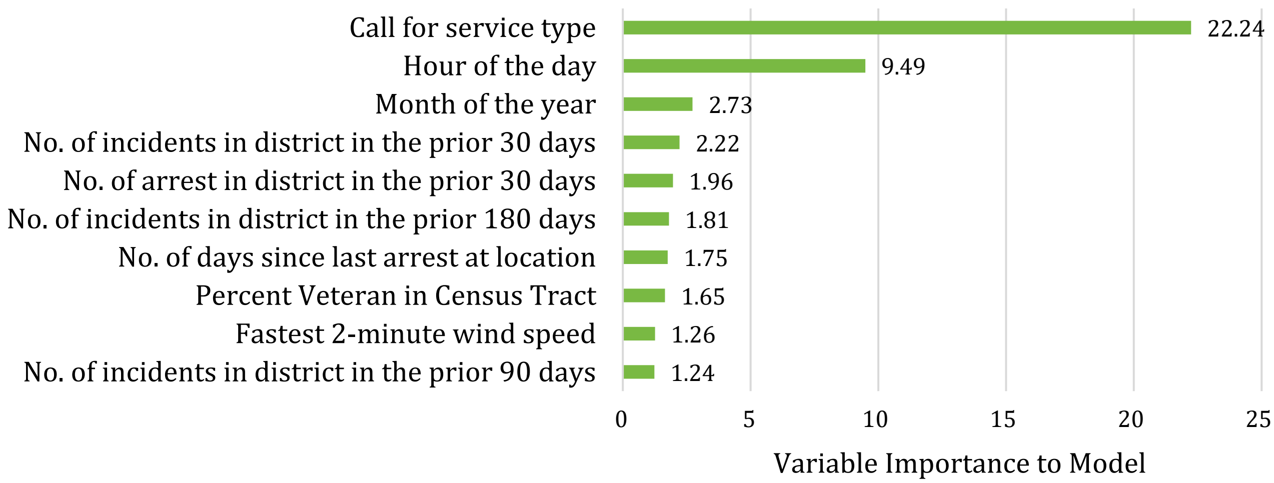
Source: Calls for service data provided by Camden County (NJ) Police Department and LEOKA officer injury data.

Figure A.2. Top 10 variables supporting model for Columbia Police Department, South Carolina



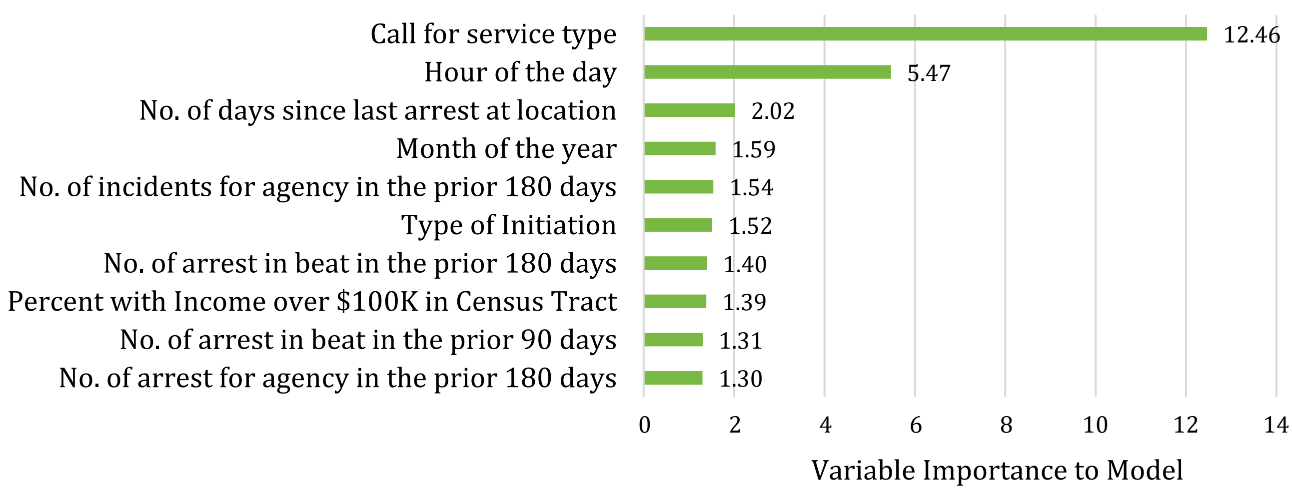
Source: Calls for service data provided by Columbia (SC) Police Department and LEOKA officer injury data.

Figure A.3. Top 10 variables supporting model for Spokane Police Department, Washington



Source: Calls for service data provided by Spokane (WA) Police Department and LEOKA officer injury data.

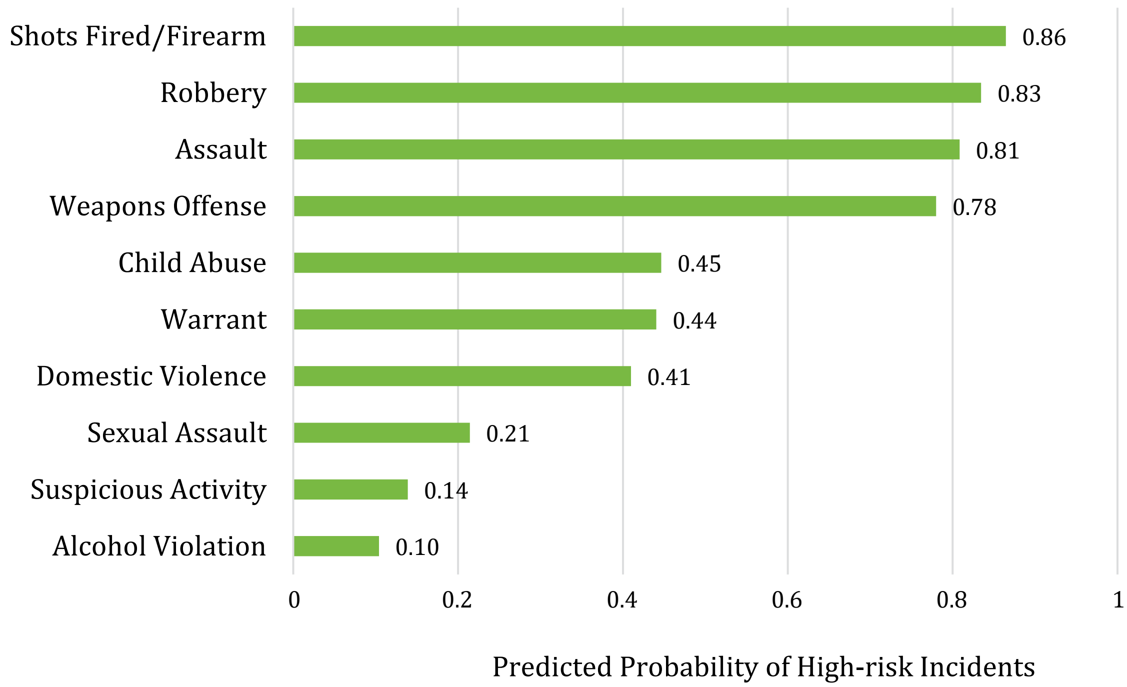
Figure A.4. Top 10 variables supporting model for Houston Police Department, Texas



Source: Calls for service data provided by Houston (TX) Police Department and LEOKA officer injury data.

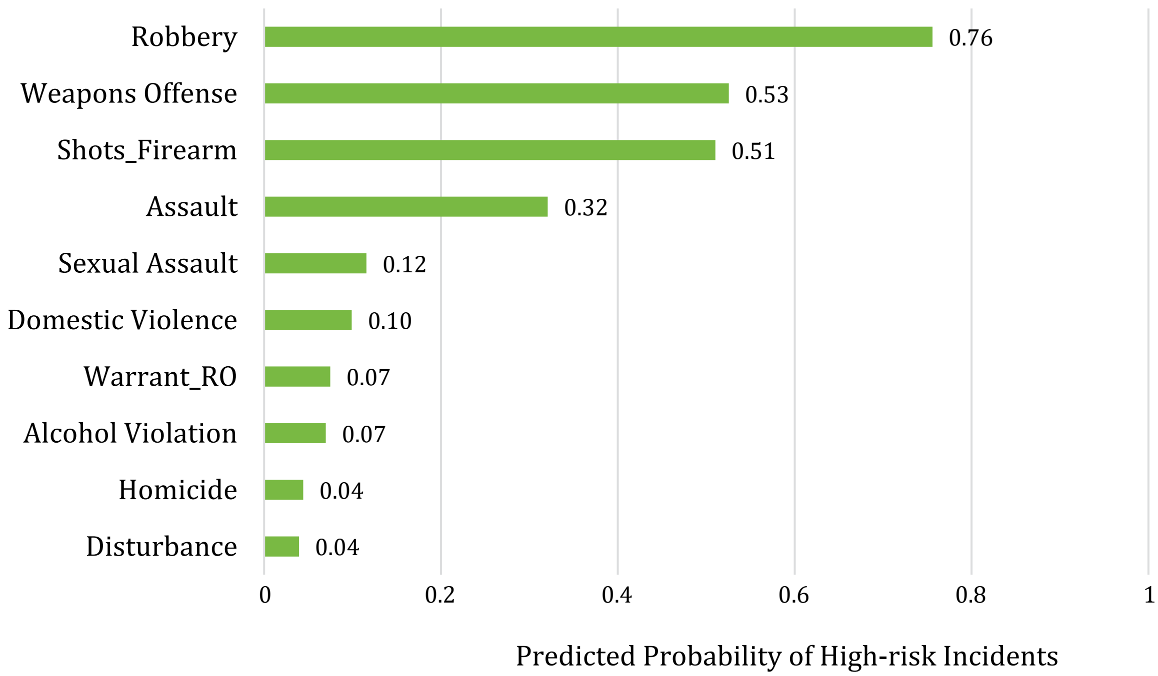
PARTIAL-DEPENDENCE

Figure A.5: Partial dependence for call for service type for Camden County Police Department, New Jersey



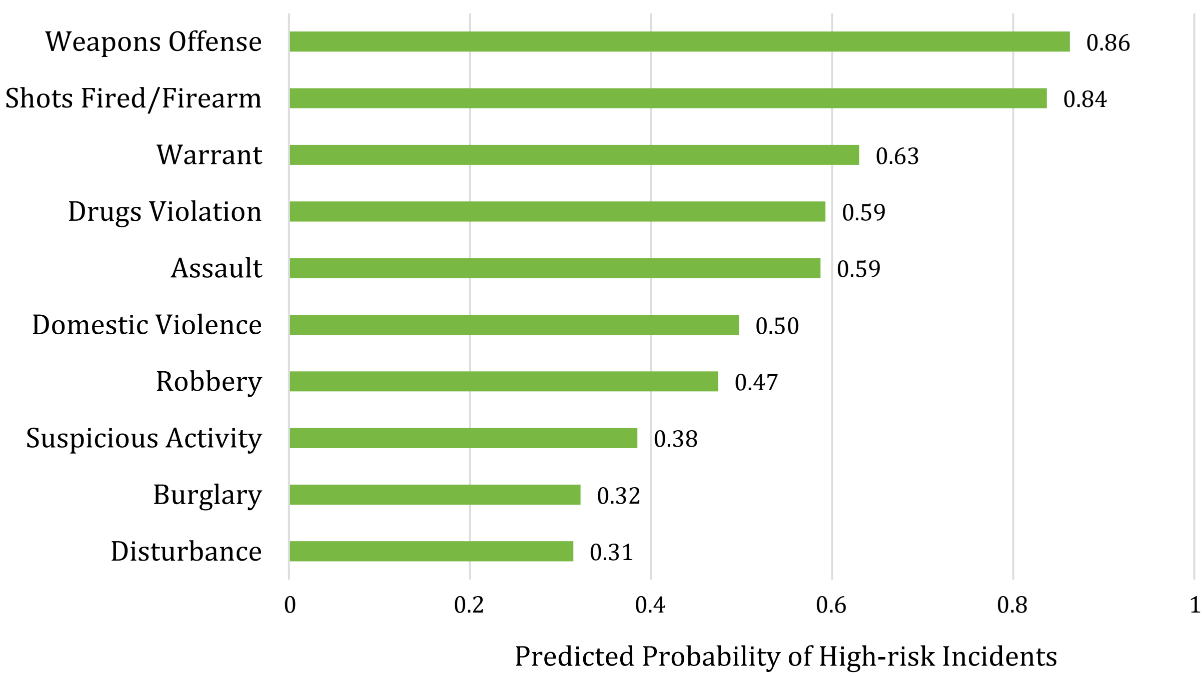
Source: Calls for service data provided by Camden County (NJ) Police Department and LEOKA officer injury data.

Figure A.6. Partial dependence for call for service type for Columbia Police Department, South Carolina



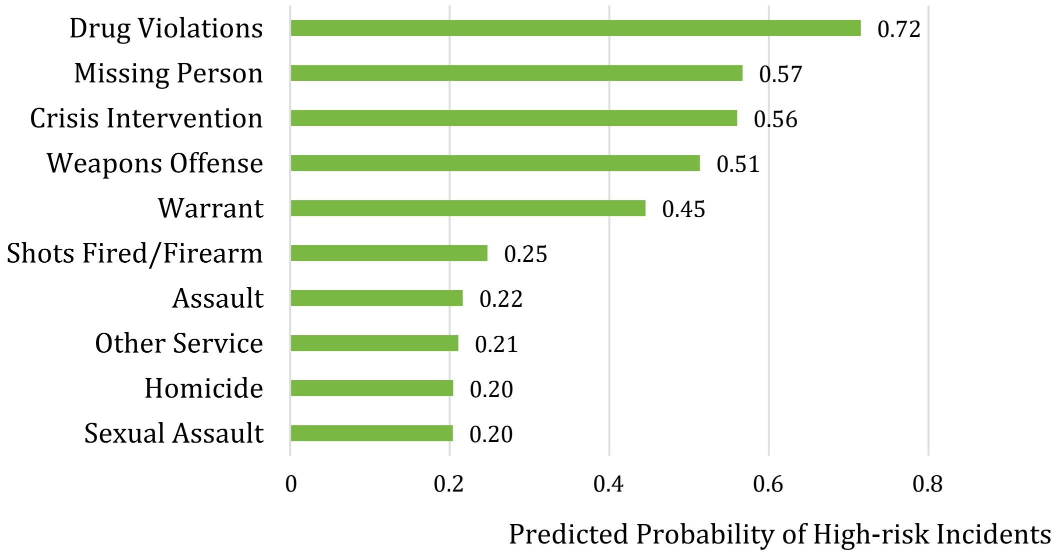
Source: Calls for service data provided by Columbia (SC) Police Department and LEOKA officer injury data.

Figure A.7. Partial dependence for call for service type for Spokane Police Department, Washington



Source: Calls for service data provided by Spokane (WA) Police Department and LEOKA officer injury data.

Figure A.8. Partial dependence for call for service type for Houston Police Department, Texas



Source: Calls for service data provided by Houston (TX) Police Department and LEOKA officer injury data.

APPENDIX B
ABOUT CNA, BJA, AND THE VALOR INITIATIVE

CNA

CNA is a nonprofit research and analysis organization dedicated to the safety and security of the nation. It operates the Institute for Public Research—which serves civilian government agencies—and the Center for Naval Analyses, the Department of the Navy's federally funded research and development center (FFRDC). CNA is dedicated to developing actionable solutions to complex problems of national importance. With nearly 700 scientists, analysts, and professional staff, CNA takes a real-world approach to gathering data, working side-by-side with operators and decision-makers around the world. CNA's research portfolio includes global security and great power competition, homeland security, emergency management, criminal justice, public health, data management, systems analysis, naval operations, and fleet and operational readiness.

BJA

BJA helps to make American communities safer by strengthening the nation's criminal justice system. Its grants, training and technical assistance, and policy development services provide state, local, and tribal governments with the cutting-edge tools and best practices they need to reduce violent and drug-related crime, support law enforcement, and combat victimization.

BJA is a component of the Office of Justice Programs, US Department of Justice, which also includes the Bureau of Justice Statistics, National Institute of Justice, Office of Juvenile Justice and Delinquency Prevention, Office for Victims of Crime, and Office of Sex Offender Sentencing, Monitoring, Apprehending, Registering, and Tracking.

BJA’s mission

BJA provides leadership and services in grant administration and criminal justice policy development to support local, state, and tribal law enforcement in achieving safer communities. BJA supports programs and initiatives in the areas of law enforcement, justice information sharing, countering terrorism, managing offenders, combating drug crime and abuse, adjudication, advancing tribal justice, crime prevention, protecting vulnerable populations, and capacity building. Driving BJA’s work in the field are the following principles:

- Emphasize local control
- Build relationships in the field
- Provide training and technical assistance in support of efforts to prevent crime, drug abuse, and violence at the national, state, and local levels
- Develop collaborations and partnerships
- Promote capacity building through planning
- Streamline the administration of grants
- Increase training and technical assistance
- Create accountability of projects
- Encourage innovation
- Communicate the value of justice efforts to decision-makers at every level

To learn more about BJA, follow them on Facebook and Twitter (@DOJBJA).

VALOR INITIATIVE

The Officer Robert Wilson III Preventing Violence Against Law Enforcement Officers and Ensuring Officer Resilience and Survivability (VALOR) Initiative is an effort to improve the immediate and long-term safety, wellness, and resilience of our nation's law enforcement officers. Through a multifaceted approach that includes delivering no-cost training (professional education), conducting research, developing and providing resources, and establishing partnerships that benefit law enforcement officers, the VALOR Initiative seeks to provide our law enforcement with innovative, useful, and valuable resources and skills.

VALOR continuously evolves to confront the many complex issues, concerns, and trends that law enforcement officers face and to integrate the latest research and practices to address all aspects of officer safety, wellness, resilience, and performance. The nature of all of these critical ongoing issues are ever-changing; many times, being driven by local, state, and national events. This can have a direct effect on an officer's ability to prevent or survive the rigorous challenges and threats that she or he may face in the line of duty.

The Department of Justice and the Bureau of Justice Assistance are dedicated to helping our law enforcement officers and the communities they serve stay safe and well. Because officer safety and community safety are intrinsically bound, requiring a strong and positive partnership, the VALOR Initiative provides a comprehensive approach to addressing law enforcement officers' needs and to building those strong and positive partnerships with the communities they serve.

Learn more about the VALOR Initiative by visiting its website.

ENDNOTES

1. Michael D. White, Lisa M. Dario, and John A. Shjarback, "Assessing Dangerousness in Policing: An Analysis of Officer Deaths in the United States, 1970–2016," *Criminology & Public Policy* 18, no. 1 (2019), pp. 11–35.

2. Our selection of the four identified agencies was based on voluntary participation. In preparation for the grant proposal, we sought collaboration with large agencies situated in geographically diverse locations. Larger size agencies will ensure a large enough sample of incident data to draw significant findings and provide sufficient explanatory power for a pilot risk assessment model. During our initial conversations with the identified agencies, we sought their input on the operational utility of the grant project to shape our grant application. Future work will include the addition of more agencies.

3. White, Dario, and Shjarback, "Assessing Dangerousness in Policing."

4. White, Dario, and Shjarback, "Assessing Dangerousness in Policing."

5. We were unable to collect this information from all project agencies across all incidents because of missing data, but whether an officer or community member initiated the call is presumably knowable for all calls for service at dispatch.

6. Although altering agency policy based on a neighborhood's characteristics poses questions about fairness, the risk assessment model will not necessarily determine that neighborhood characteristics are important predictors, and findings in either direction will help inform understanding of officer safety.

7. United States Census Bureau, "U.S. Census Bureau QuickFacts: Camden city, New Jersey," https://www.census.gov/quickfacts/camdencitynewjersey.

8. United States Census Bureau, "U.S. Census Bureau QuickFacts: Columbia city, South Carolina," https://www.census.gov/quickfacts/columbiacitysouthcarolina.

9. United States Census Bureau, "U.S. Census Bureau QuickFacts: Spokane city, Washington," https://www.census.gov/quickfacts/fact/table/spokanecitywashington,US/PST045219.

10. SPD changed its records management system and was able to provide only three years of data during the project period of performance.

11. United States Census Bureau, "U.S. Census Bureau QuickFacts: Houston city, Texas," https://www.census.gov/quickfacts/fact/table/houstoncitytexas,US/PST045219.

12. HPD was only able to provide data only up through 2018 for analysis during the project period of performance.

13. Richard A. Berk and Justin Bleich, "Statistical Procedures for Forecasting Criminal Behavior: A Comparative Assessment," *Criminology & Public Policy* 12, no. 3 (2013), p. 513; Tim Brennan and William L. Oliver, "Emergence of Machine Learning Techniques in Criminology: Implications of Complexity in Our Data and in Research Questions," *Criminology & Public Policy* 12, no. 3 (2013), p. 551; Samuel Carton et al., "Identifying Police Officers at Risk of Adverse Events," in *Proceedings of the 22nd ACM SIGKDD International Conference on Knowledge Discovery and Data Mining*, 2016, 67–76.

14. Alexander Babuta, Marion Oswald, and Christine Rinik, *Machine Learning Algorithms and Police Decision-Making: Legal, Ethical and Regulatory Challenges*, Royal United Services Institute for Defence and Security Studies, 2018; Andrew D. Selbst, "Disparate Impact in Big Data Policing," *Georgia Law Review* 52, no. 109 (2017).

15. Babuta, Oswald, and Rinik, *Machine Learning Algorithms*; Berk and Bleich, "Statistical Procedures," p. 513; Carton et al., "Identifying Police Officers."

16. Kevin P. Murphy, *Machine Learning: A Probabilistic Perspective* (Cambridge, MA: MIT, 2012).

17. Berk and Bleich, "Statistical Procedures," p. 513.

18. Berk and Bleich, "Statistical Procedures," p. 513.

19. We counted blades and firearms as weapons because they are especially dangerous; we did not count fists or everyday objects because the choice to use these objects as weapons is the danger, not their presence.

20. The **Using Analytics to Improve Officer Safety** Advisory Group provides guidance on the development of the pilot risk assessment model, including validation of indicators and categorization of risk. All Advisory Group members were selected based on their expertise in police operations and procedures, as well as risk modeling and risk assessment analytics within the criminal justice field.

21. André Altmann, Laura Toloşi, Oliver Sander, and Thomas Lengauer, "Permutation Importance: A Corrected Feature Importance Measure," *Bioinformatics* 26, no. 10 (2010), pp. 1340–1347.

22. Christoph Molnar, *Interpretable Machine Learning* (Lulu.com, 2020).

23. S. Rebecca Neusteter et al., *The 911 Call Processing System: A Review of the Literature as It Relates to Policing* (Washington, DC: Vera Institute of Justice, 2019).

24. An example of call scripts used in Eugene, Oregon, can be found at https://www.eugene-or.gov/2892/9-1-1-Call-Scripts.

25. More information about the Edward Byrne Memorial Justice Grant can be found at https://bja.ojp.gov/program/jag/overview.

26. More information about the Patrick Leahy Bulletproof Vest Partnership can be found at https://ojp.gov/program/bulletproof-vest-partnership/overview.

27. Centers for Disease Control and Prevention, "Law Enforcement Officer Motor Vehicle Safety," https://www.cdc.gov/niosh/topics/leo/default.html.

28. Nick Breul and Desiree Luongo, *Making It Safer: A Study of Law Enforcement Fatalities Between 2010–2016*, Office of Community Oriented Policing Services, 2017, https://www.leonearmiss.org/wp-content/uploads/2018/03/COPS_Making-it-Safer_Study-of-2010-2016-Fatalities_032618.pdf.

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