



Justice Insights Series: Research Briefs for Policy and Practice

Can Machine Learning Forecast Which 911 Calls Put Officers at Greatest Risk?

Key Takeaways

- Researchers used information available at the time of dispatch to forecast whether a 911 call involving weapons would pose high risk or low risk to responding officers.
- For about half of a set of test calls, the forecasting tool could not reliably distinguish between high and low risk. The researchers argue that this inconclusive result is appropriate when the data are insufficient to support a confident forecast.
- The number of 911 calls from the same neighborhood in the past 30 days was by far the strongest predictor of risk, accounting for about 80 percent of the forecasting tool's predictive power.

Why This Matters

Policing is a high-risk occupation in which officers routinely face hostile citizens, volatile situations, and physical hazards. Agencies invest heavily in protective gear (such as body armor) and tactical training but pay far less attention to the first link in the emergency response chain: the 911 communications center.

When a call comes in, 911 professionals act as gatekeepers and risk appraisers. They extract details, assess risk, and transmit information that shapes an officer's mental readiness. Call takers and dispatchers, however, face fatigue, overload, and time pressure, and they must often relay information without confirming details from callers. As the article summarizes, communication errors and subjective risk appraisals can leave officers dangerously under prepared or unnecessarily over prepared. A data-driven, objective method to forecast dispatch risk can help bridge this gap. By using routinely collected information to forecast officer risk before units arrive at the scene, agencies can better anticipate low-probability, high-cost safety incidents and support better informed decisions about how officers should prepare and respond.

No prior study had used dispatch information to build a forecasting model aimed specifically at predicting officer risk for individual calls. This study tested the feasibility of using machine learning, combined with conformal prediction methods, to forecast risk using data available to call-takers and dispatchers at the onset of a call.

How the Study Worked

The researchers partnered with the Camden County Police Department in New Jersey and analyzed every 911 call for service from January 1, 2015, through December 31, 2019—about 105,000 calls per year. Because severe safety incidents are rare relative to the total call volume, the team grouped calls into broad crime categories and focused its analysis on 1,928 calls involving weapons offenses. From these calls, the researchers generated 81 potential predictors that a call taker or dispatcher could know quickly, excluding information available only after officers arrived on scene. These predictors included the crime type listed in the dispatch, the date and time of the call (day of week, month, season, and time of day) weather conditions, local crime and call-for-service trends (such as recent arrests and call volume in the same police sector). The researchers labeled a call as high risk if it involved an officer injury, a fleeing or resisting suspect, a suspect with a weapon, or a crime still in progress. All other calls were labeled low risk.

To build and evaluate the forecasting tool, the researchers randomly split the data into a training set, used to develop the algorithm, and a separate testing set, used to assess how well the forecasting tool performed on new data. This approach avoids overstating accuracy by evaluating the model on data separate from those used to build it.

The researchers applied a machine learning classifier (stochastic gradient boosting) and incorporated a ten-to-one cost weighting ratio, treating an unexpected high-risk encounter for an officer as roughly ten times more costly than an overprepared false alarm. This weighting placed greater emphasis on avoiding missed high-risk calls.

Finally, the researchers used nested conformal prediction sets on a random holdout sample of 100 calls. Instead of forcing a simple yes-or-no forecast, this method estimates how confident the algorithm is in labeling a call as high or low risk and allows it to return a “can’t tell” result when the evidence is too weak to support a reliable forecast.

What Was Learned

- **For weapons-related dispatches, the algorithm produced confident, accurate forecasts.** In a 100-call holdout sample, the algorithm forecast high risk for about a quarter of the calls and low risk for another quarter, with odds of at least three to one that each of those forecasts was correct.
- **For the rest, the algorithm correctly reported that it could not tell.** About half of the test calls fell into this “can’t tell” category. The researchers treat this “can’t tell” category as a valid and appropriate result rather than a failure.
- **The number of 911 calls from the same neighborhood in the past 30 days dominated the forecasts,** accounting for about 80 percent of the model’s predictive power.
- **The day of the week, season, and time of day also influenced risk.** Consistent with prior research, the study found greater risks to police officers on weekends, during evenings, and during the summer months.

What This Means in Practice

This study shows that useful, objective risk forecasting is technically achievable using existing dispatch data and available machine learning tools. At the same time, the substantial share of “can’t tell” forecasts underscores that current data limit how confidently agencies can classify risk for many calls. Police departments that consider forecasting tools must establish clear policies on how dispatchers and officers should handle “can’t tell” scenarios, such as defaulting to safety precautions or factoring in qualitative cues such as a caller’s tone of voice or specific phrases.

Richer data (e.g., suspect’s age and gender, whether drugs or alcohol appear involved), could improve accuracy. Decisions about how to treat “can’t tell” forecasts, how to balance the cost of missing a real risk against the cost of a false alarm, and how to train dispatchers and officers to use the tool are policy choices that each police department would need to resolve before any real-world implementation.

Source article

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