Applying Large Language Models to Extract Case Clearance Factors from Police Detective Narratives

Introduction.

Approximately 48,000 people die from firearm-related deaths in the United States annually, with nonfatal firearm injuries being three times more prevalent.[1,2] While police departments investigate both homicides and nonfatal shootings (NFS), there is a stark disparity in case clearance (i.e., if the offender is arrested or not).[3] Approximately 61 percent of homicides are solved in the US annually,[4] but only one in ten NFS cases result in an arrest.[5] Unsolved shootings leave survivors and communities without justice and closure, and the potential for deterrence of future firearm violence that clearance can provide.

Much of the literature on solving firearm crimes has focused on improvements in homicides, or has focused on detective processes and department resources.[5,6] Lower detective caseloads and increased investigative resources (e.g., analysts, specialized unit collaboration) contribute to higher homicide case clearances.[7] NFS cases, however, have fewer clearances largely due to uncooperative witnesses unwilling to talk to the police.[8] Less research focuses on understanding the factors leading to nonfatal shooting case investigations that result in case clearances, meaning there is a critical gap in our current understanding of modifiable mechanisms that could improve NFS case clearance outcomes.

To improve NFS case clearance, we leverage access to a rare dataset: narrative case files from a major Midwestern police department which contain granular, unstructured, documentation of detective interactions with victims and witnesses. We develop large language models (LLMs) to systematically identify why some firearm crime investigations succeed while others do not, considering mechanisms such as victim cooperation and available evidence. To our knowledge, this is one of the first applications of LLMs to police investigation reports.

Data and Methods.

We use unstructured narratives from the closed (completed) detective files from 2020-2024 as text input to classify circumstances and mechanisms that drive case clearances. We will measure outcomes including whether a victim cooperates or not, if witnesses were present, whether witnesses are willing to cooperate, the presence of forensic or surveillance evidence, and expressions of fear of retaliation.

To classify outcomes, we will use open-source large language models (LLMs) that are able to run locally without requiring sensitive transfer of data.[9]

We start by labeling training data of approximately 10% of the full sample, consisting of 42 nonfatal shooting cases. While we primarily label these cases in order to evaluate prediction accuracy, the random sample attributes are informative. We present descriptive statistics from training data labeling.

Preliminary Results.

We labeled 39 closed detective files from 2020 to 2024. Witnesses were present in 31 of 39 cases (79.5%), and 22 (56.4%) had multiple witnesses. Among the 31 cases with a witness, witnesses named a suspect in 23 (74.2%). Victims cooperated in 33 cases (84.6%) and named a suspect in 30 (76.9%). Two victims did not know the assailant (5.1%), and two were not interviewed because they were hospitalized or incapacitated (5.1%).

Surveillance footage was documented in 11 cases (28.2%). Social media played a role in the arrest in 3 cases (7.7%). Domestic violence was involved in 10 cases (25.6%).

Table 1. Case Attributes of Random Sample

Witness present	**39**	**100.0%**
None	8	20.5%
One	9	23.1%
Multiple	22	56.4%
Witness named suspect (among cases with a witness)	**31**	**100.0%**
Yes	23	74.2%
No	5	16.1%
Not applicable/unclear	3	9.7%
Victim cooperated	**39**	**100.0%**
Yes	33	84.6%
No	1	2.6%
Victim did not know assailant	2	5.1%
Victim not interviewed (hospital/incapacitated)	2	5.1%
Not applicable	1	2.6%
Victim named a suspect	**39**	**100.0%**
Yes	30	76.9%
No	8	20.5%
Not applicable	1	2.6%
Surveillance footage	**39**	**100.0%**
Yes	11	28.2%
No	26	66.7%
Not applicable	2	5.1%
Social media played a role in arrest	**39**	**100.0%**
Yes	3	7.7%
No	35	89.7%
Not applicable	1	2.6%
Domestic violence involved	**39**	**100.0%**
Yes	10	25.6%
No	27	69.2%
Missing	2	5.1%

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