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Examining the Relationship Between Weapon Type and Relationship Type in American Homicides: A Bayesian Approach

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Abstract

The weapon type used in a homicide predicts the victim-perpetrator relationship. However, there are some limitations in this past research including the common data analytic strategies. Our purpose was to build a model of weapon type, predicting relationship type, and to address previous limitations. We examined 363,927 homicides and used Bayesian multilevel categorical regression. In addition to analyzing weapon type (final model consisted of 16 weapon categories), we examined the victims' sex, age, and race as covariates and modeled the data across states and counties. Results indicate that weapon type is highly informative, however, the age of the victim and sex of the victim interact in important ways.

Keywords

homicide, weapons, Bayesian statistics, multilevel models, categorical regression

Introduction

Predicting what kind of relationship a homicide victim and perpetrator have, using details from the crime scene, is a practical question that concerns all homicide investigators. For example, if a detective knows the suspect is likely to be an acquaintance, then that could help to steer the time sensitive investigation, by prioritizing investigating a victim's neighbors, friends, employer, etc. One variable that has received some consideration in understanding victim- perpetrator relationship, is the type of weapon

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used in the homicide. If a homicide detective could increase the chances of correctly identifying the suspect by knowing the strength of the relationship between weapon type and relationship type, then this information is potentially valuable. Further, it seems that homicide detectives consider a variety of crime scene evidence when trying to predict who is the perpetrator. If this is helpful or harmful, partly depends on the veracity of the relationship. Past research on this topic exists, but some of the inferences that can be drawn are limited due size of the homicide database, the necessity of collapsing across categories (e.g., combining different weapons types into one group), and choice of statistical procedure. This research analyzes over three decades of homicides from the Federal Bureau of Investigation's Supplementary Homicide Reports (SHR) and homicides not reported to the FBI, but obtained through the Freedom of Information Act, by the Murder Accountability Project (Hargrove, 2019). In this research, Bayesian statistics are applied to model the relationship between weapon type and relationship type and how it may change due to a victims age, sex, and race. By analyzing a larger set of cases, including more weapon types, and applying a more advanced statistical approach, this research makes a substantial contribution by allowing us to build a predictive model and produce parameter estimates that are more intuitive.

Victim–Perpetrator Relationship

There is no single scheme for categorizing the victim-perpetrator relationship, but regardless of scheme, there is typically a distinct pattern within homicides. According to the 2017 data from the National Incident based Reporting System (NIBRS), the most common relationship type (38%) is, *known to victim and other*, which means that the victim and perpetrator knew each other, but were not related. Additional categories include *family members* (15%), *family members and other* (1%), *stranger* (10%), *and all other* (37%). In the Supplementary Homicide Report there are 28 relationship categories, with three main groups, family member, acquaintance outside the family, and victim not known to the offender. However, there are a variety of ways researchers collapse or combine categories. For example, in describing homicide trends in the US, Cooper and Smith (2011) used multiple categorization schemes including stranger, spouse, other family, boyfriend/girlfriend, and other acquaintance. Although the majority of cases did not have a known victim-perpetrator relationship, among those that did, approximately half were cases in which the perpetrator was an acquaintance. Similarly, Morgan and Kratcoski (1986) found that the majority of homicide victims were killed by someone who was not a stranger, although the proportion of stranger to non-stranger killings does fluctuate over time. Just as there are a variety of victim-offender relationship types and categorization schemes, so too are there a variety of weapons used in homicides.

Weapon Type

Data from NIBRS (United States Federal Bureau of Investigation, 2017a 2017b) has five groups of weapons (for homicide offenses), firearms, knife/cutting instrument, personal weapons, and all other. The most common in 2017 was firearms (67%), with handguns being the most common sub-group (see also Hargarten et al., 1996). Use of a knife or other cutting instrument is common (10%). Rare weapons would include, for example, poison and explosives. In the SHRs there are 17 total categories: Asphyxiation (includes death by gas), blunt object (hammer, club, etc), fire, firearm (type not stated), handgun (pistol, revolver, etc), knife or cutting instrument, narcotics (or drugs, sleeping pills), other gun, other or type unknown, personal weapons (includes beating), rifle, shotgun, strangulation (hanging). Some past research has found an association between weapon type and victim-perpetrator relationship.

Firearm use has been more associated with acquaintances and strangers, compared to intimate partner relationships and family members (Fox & Zawitz, 1999). Fox and Allen (2014) found that males are most associated with firearms when the homicide victim is a nonfamily member who is also male. Trojan and Krull (2012) found that intimate partner relationships (former/current) were more likely to involve stabbings than any other relationship type, and that intimate partner relationships were less likely to involve firearms. The use of manual violence was more characteristic of intimate and family/friends compared to acquaintances and strangers. Specifically examining spousal homicides, Allen and Fox (2013) found that for firearms, older husbands are overrepresented as victims, and for knives, younger husbands are overrepresented as victims. Examining sexual homicides, Chan and Heide (2008) found that when killing adolescents, juvenile killers tended to use contact and edged weapons and adult killers tended to use personal weapons. Lastly, Reynolds et al. (2019) found that when sharp force trauma, blunt force trauma, or asphyxiation, was the cause of death, relative to shooting, it was more likely that the perpetrator was a stranger relative to an acquaintance. When multiple means were used in the homicide, sharp force trauma, or asphyxiation, relative to shooting, the perpetrator was more likely a stranger relative to having a close relationship. While several studies do find an association between relationship type and weapon type, there is some inconsistency.

In an analysis of sexual homicide offenders, Chan et al. (2013) classified relationships as intimate partner, family member, acquaintance, and stranger. Five categories of weapons were used, personal weapon, contact weapon (blunt object), edged weapon, firearm, and other weapon. Results from a chi-squared analysis found almost no relationship between weapon type and victim–perpetrator relationship (Cramer's $V=0.07$, $N=3{,}738$). Similarly, in a sample of 57 homicide cases, Drawdy and Myers (2004) found no relationship between victim- perpetrator relationship and weapon choice. Results from Drawdy and Myers (2004) could be explained because of low sample size. However, the results from Chan et al. (2013) are not likely driven by sample size.

Despite some inconsistency in the effects, the literature in general seems to suggest a relationship between relationship type and weapon type. Perhaps the most consistent finding, is that stranger killings are most associated with firearms. This may in part be due to gang or other criminal related activity. Egley et al. (2012) found that gang related homicides are more likely to involve firearms and suggested that they are often retaliatory actions. Pizarro et al. (2019) also found that firearm homicides are more likely with drug or gang activity.

It should be clear however, that when examining the relationship between weapons and relationship type, there are a variety of questions one might ask. Some of the previous research, for example Trojan and Krull (2012), only looked at cross-tabulations, not how one variable could be used to predict another (see also Decker, 1996). Other research has examined how relationship impacts weapon choice. Pizarro et al. (2019) examined how factors like relationship type (intimate/family, friends/acquaintances, and stranger) predicted weapon choice (other, cutting/blunt object, firearms; see also Pelletier & Pizarro, 2019). Still other research examines specific types of homicides. Heide (1993) investigated the different types of weapons used by juveniles versus adults to kill their parents. Similarly, Chan and Heide (2008) examined different types of weapons used by juveniles versus adults in sexual homicides, with evidence supporting Heide's (1993) physical strength hypothesis that the strength differential between offender and victim, may play a role (see also Chan & Frei, 2013). There has been comparatively less research aimed at modeling how weapon type predicts relationship type, when accounting for other victim variables. This is the more informative area from the perspective of the investigator. That is, what is useful for investigators, is knowing how the type of weapon used in the homicide (and other victim information), predicts what relationship the victim and perpetrator have. This question motived the current research.

As this research took the perspective of the investigator, it is worth noting that understanding how weapon type predicts relationship type is also important to understand because investigators may *think* that knowing the weapon tells them who the offender is, and thus could influence their investigation. A useful parallel may be in deception detection. While officers *think* they can detect deception, the evidence indicates otherwise (Aamodt, 2008; Aamodt & Custer, 2006; DePaulo & Pfeifer, 1986; Vrij & Mann, 2001) and it is important that officers are therefore not overly confident in their ability to tell if someone is lying. While there are many factors that may affect the decision-making process of detectives, there is evidence that they attend to features of the crime scene, such as the weapon used, to generate hypotheses as to who is the offender. For example, Wright (2013) showed 20 homicide crime scene photographs to 40 homicide detectives. A "think aloud paradigm" was used, and detectives were asked to categorize the crime based on the available information. Using a qualitative content analysis, Wright (2013) found that detectives explicitly considered aspects like method of death and location of the homicide, generated hypotheses, and made inferences as to what type of homicide it might be (e.g., crime related vs. domestic homicide). While only self-report, detectives did indicate that the process was similar to how they investigate actual homicides. This evidence suggests that detectives already think that weapon type can be used to predict the victim-perpetrator relationship. It is critical therefore, to precisely understand the nature of the relationship between weapon type predicting relationship type, and communicate that in an effective way.

Current Research

The purpose of this research is to build a model predicting relationship type, using weapon type and other victim variables, and address some limitations present in the existing literature. One limitation in past research has been sample size. Because the comparisons are between multichotomous categories, having relatively large samples sizes is important. Indeed, one potential cause for the discrepancies in this literature is the use of small sample sizes, such as in Drawdy and Myers (2004). Thus, this research aimed to address this by examining a larger and more comprehensive homicide database.

A second limitation in past research has been choice of statistical procedure. Past research in this area have used simple cross-tabulations, frequentist methods such as chi-square (as well as more advanced chi-square methods, see Chan & Beauregard, 2016) and multinomial logistic regression (e.g., Chan et al., 2013; Reynolds et al., 2019), as well as correspondence analysis (e.g., Fox & Allen, 2014). These are all reasonable statistical approaches to understand the relationship between weapon type and victim-perpetrator relationship. For example, a correspondence analysis is appropriate when the goal is to describe the relationships between rows and columns of a contingency table and allows one to graph the relationships, with those coordinates being similar to the components in a principal component analysis (Greenacre & Blasius, 1994; Heijden et al., 1989; Hoffman & Franke, 1986). However, there are some issues.

First, the results of such data analytic techniques may not be particularly intuitive. The crux of the frequentist approach is the *p*-value, a statement concerning probability, specifically, the probability of data given a null hypothesis. However, perhaps because of the non-intuitive definition of probability, p-values are often misinterpreted by social scientists (Goodman, 2008). One value of understanding the nature of the relationship between weapon type and victim-perpetrator relationship, is the application of the information in real cases by detectives. If detectives cannot make sense of the results, then information cannot be used effectively. Moreover, detectives may reasonably misinterpret the results. Based on some of the above literature, there seems to be a relationship between stranger killers and firearms. However, it would be incorrect to conclude that if a firearm death occurs the likely killer is a stranger. The base rate for stranger homicides is still relatively low. Due to the nature of the statistics and that the results are often presented as tables of coefficients (rather than plots), an intuitive interpretation of the results is difficult.

Second, the statistical techniques may not be able to capture, and therefore make use of, the complexity of the data structure. Weapon laws are different in each of the 50 states in the US, and certain regions of the country are more restrictive in their weapon laws. Thus, some correlation may occur in weapon use in nearby cities, counties, and states. Correspondence analysis, chi-square, and multinomial regression cannot account for such variation. This is not a trivial concern. On the other hand, Bayesian multilevel multinomial regression does not have these disadvantages and also confers several advantages (see Dienes, 2011; Kruschke & Liddell, 2018).

Rather than focusing on the probability of data given a null hypothesis, in Bayesian statistics, all kinds of uncertainty, both those in the data and in the model parameters, are expressed using probability. In particular, this applies to the uncertainty in the model parameters after taking into account the information in the data (i.e., the posterior distribution). Quantifying uncertainty using probability is arguably more intuitive than measures such as the *p*-value. It is possible therefore, that these results might be more easily understood and used by actual homicide detectives. It would be useful, for example, for homicide detectives to know how much the probability changes that it is one type of suspect versus another, because of the type of weapon used. This is precisely the information that Bayesian statistics yields, and therefore, we argue, is well suited to address our research question.

Furthermore, using Bayesian statistics and multilevel modeling, we can examine in more detail, complex effects, that are not well captured in techniques such as chi-square or correspondence analysis. This allows us to extend the understanding of weapon type and relationship type more easily to include effects that contain other victim information available at the crime scene, such as victim's sex, age, race, and their interaction. Therefore, this research can make a substantial contribution by going beyond simple associations, to building a predictive model.

Data

This research used data from FBI's SHR (1976–2017). The SHR contains official homicides that have been investigated by police around the country and reported to the FBI. The SHRs are generally considered one of the most comprehensive sources for homicides that contain simple victim and offender details, such as age, sex, weapon used, and relationship between victim and offender. Our data from the SHR contains 742,210 homicides. One limitation of the data from the FBI is that it contains only reported cases. To address this and analyze a more inclusive data set, an additional 28,815 homicides were analyzed ($N=771,025$). Data were obtained from the Murder Accountability Project (MAP), who obtained the cases through the Freedom of Information Act (Hargrove, 2019). The MAP is a nonprofit group that gives police and the general public information on homicide, and has even developed an algorithm for identifying suspicious clusters of murders that could be the result of a serial killer. As these cases represent homicides not reported to the Justice Department, there is no overlap. Cases from the MAP use essentially the same coding and categories as the FBI (e.g., weapon type, victim-offender relationship type, victim's race are the same as used in the FBI; see data dictionary at http://www.murderdata.org). Differences include the addition of a unique record identifier generated by MAP, if the crime was solved, and the source of the data. Victim's age has been modified to simplify calculations. Specifically, the category BB (7 days old to 364 days old) and NB (birth to 6 days old) has been changed to a value of zero, indicating the victim had not lived a full year of life. Conveniently, the MAP have created a combined system in which users may search online or download all the data using the modified coding system. The MAP claim to have the most complete data on homicides in the United States currently available. It is this pooled data containing both officially reported cases (SHR) and unreported cases (obtained by the MAP using the Freedom of Information Act) that constitutes the current dataset.

Data Processing

The 771,025 homicides were not all relevant or useful for our purposes. To filter the data, we first excluded all unsolved homicides, as those will not have victim and perpetrator relationships (N=544,488). Next, we removed cases that had multiple victims or multiple offenders, meaning we only included single victim/single offender homicides (N=421,536). There are logistical issues in the coding of these types of cases (see Fox & Allen, 2014; Maltz, 1999) and they are sometimes a qualitatively different form of homicide (e.g., mass murder). Lastly, we removed homicides in which the relationship between victim and offender was labeled as "Relationship not determined". The final data set for analysis included 363,927 homicides.

Variables

Victim's race. The majority of the victims were White (52.5%), followed by Black (44.54), Asian (1.34%), American Indian/Alaskan Native (.91%), Unknown (.71%), and Native Hawaiian/Pacific Islander (.01%). Victim ethnicity was collinear with race, and therefore was not included in analyses.

Victim's age. Victims had an average age of 33.34 years (SD=16.64, Mdn=30).

Victim's sex. The majority of the victims were male (72.9%), followed by female (27.07%), and unknown (.03%),

States. All 50 states in America and the District of Columbia were represented.

Weapon type. There were 16 categories of weapons included. The only category not included was motor vehicle/vessel, as there was only one case. The most common type was handgun—pistol, revolver, etc. (46.83%). The next most common was knife/cutting instrument (18.86%), personal weapons—includes beating (7.71%), shotgun (6.68%), rifle (4.8%), blunt object—hammer, club, etc. (4.51%), firearm—type not stated (3.67%), Other—type unknown (3.59%), strangulation—hanging (1.12%), asphyxiation (.7%), fire (.53%), narcotics—drugs, sleeping pills (.38%), drowning (.25%), other gun (.2%), poison—does not include gas (.08%), Pushed/thrown out window (.05%), and explosives (.03%).

Victim–perpetrator relationship. There were 28 relationship categories. Based on past research and the difficulty in fitting a model with 28 categories, relationships were classified into three groups: *family member* (husband, wife, mother, father, sister, brother, common-law husband, and common-law wife), *acquaintance* (neighbor, friend, employer, employee, current and former boyfriend/girlfriend, and ex-husband/ex-wife) and *stranger*. One reason for reducing categories is that it eliminates potential confounding in the acquaintance category as victims could fit into multiple subgroups (e.g., friend or employee; Fox & Allen, 2014). The most common relationship type was acquaintance (54.95%), followed by family (25.47%), and lastly stranger (19.58%). The reference category for the outcome variable used in the Bayesian multinomial regression models was "stranger".

Results

Analytical Strategy

Data analyses were conducted using the programming language R (R Core Team, 2019) with the RStudio interface (RStudio Team, 2018). We applied several tidyverse packages (Wickham, 2019) for data preparation and plotting as well as the brms package (Bürkner, 2017), which is based on the probabilistic programming language Stan (Carpenter et al., 2017) for the actual modeling and inference.

Multinomial models of varying complexity were fitted starting from using only the weapon type as predictor (initial model), and then adding main effects and interactions of victim variables (i.e., age, sex, and race), to including multilevel structure over states and counties. The interaction between weapon type and victim race was not modeled as it turned out to be computationally infeasible due to the large number of additionally required regression coefficients. The final model was estimated on the basis of a subset of 100k observations to keep the computational effort feasible (up to 5 days per model on a high-performance computing cluster).

Weakly informative prior distributions were chosen to provide some regularization for the model without strongly influencing parameter estimates (Gelman et al., 2013; see supplemental material for details: osf.io/f52cp/). All models were fitted using 20 independent Markov chains each with 400 iterations of which the first 250 were warmup. This led to a total of 3,000 post-warmup posterior samples used for inference. According to standard convergence diagnostics, all models converged (Rhat < 1.05; Vehtari et al., 2020) with sufficient precision for our inference purposes (effective sample size of at a least a few hundred for most coefficients; see supplemental materials).

Using the random subset of 100 k observations, we ran multiple models of increasing complexity, starting with a model using only weapon type as a predictor. In the following steps, we consecutively added main effects and interactions of victim variables as well as multilevel terms of states and counties (see supplemental material). Some of the simpler models were also fitted using the full data (–364 k observations; see supplemental material) but especially the multilevel models turned out to be computationally infeasible in this case (computation time exceeding the maximum of 5 days per job on the high-performance computing cluster). In the plots discussed below, posterior predictions of estimated quantities are displayed in the form of the posterior means and 95% central credible intervals, the latter depicting the range in which the estimated parameters lie with 95% probability.

Initial model. An initial model was run using only weapon type as a predictor. In Figure 1, we show the obtained posterior estimates on the basis of the full data.

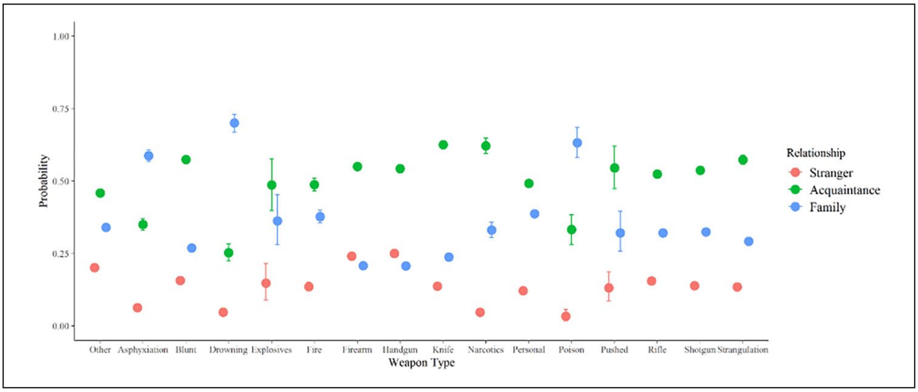

Figure 1. Parameter estimates from the full data set on the simple model of weapon type predicting relationship category (initial model). The category labeled firearm refers to "firearm—type not stated".

Final model. Model comparisons based on approximate leave-one-out cross-validation (Vehtari et al., 2017) indicated the best fit for the multinomial model with overall effects and interactions between weapon type and victim variables as well as varying intercepts, but no varying slopes, across states and counties (see supplemental material). The R formula for the final model was: *Relationship ~ (Weapon + VicRace) * VicSex * VicAge + (1 | State) + (1 | County)*. Due to page limitations, we only show the plots for the interactions between victims' age, victims' sex, and weapon type, and focus on those results. For other effects, please see supplemental material.

Younger males and females. For younger males, the most likely perpetrator, in most weapon types, was an acquaintance (Figure 2). However, for some weapon types, the pattern diverged. For example, in cases of asphyxiation and poisoning, the most likely perpetrator was a family member. On the other hand, for younger female victims, family members tended to be the most likely perpetrator (Figure 3). Particularly in cases where poison or drowning was used, the probability was very high that the perpetrator was a family member. However, in cases where a handgun, knife, or strangulation was used, the perpetrator was most likely to be an acquaintance.

Average age males and females. As males age, the perpetrator was still likely to be an acquaintance, particularly in cases of drowning, narcotics, and strangulation (Figure 4). However, for average aged males, asphyxiation predicted a higher probability of the perpetrator being an acquaintance, whereas for younger males it was a family member. In general, for average age males, in most weapon types, family members were unlikely suspects, particularly where a handgun was used. However, it depends on the weapon type, with poison, for example, predicting family members to be more likely. As females age, most of the weapon effects were similar (Figure 5). For example, in most weapon types, strangers were unlikely perpetrators. As with younger females, family members tended to be the most likely perpetrator in most

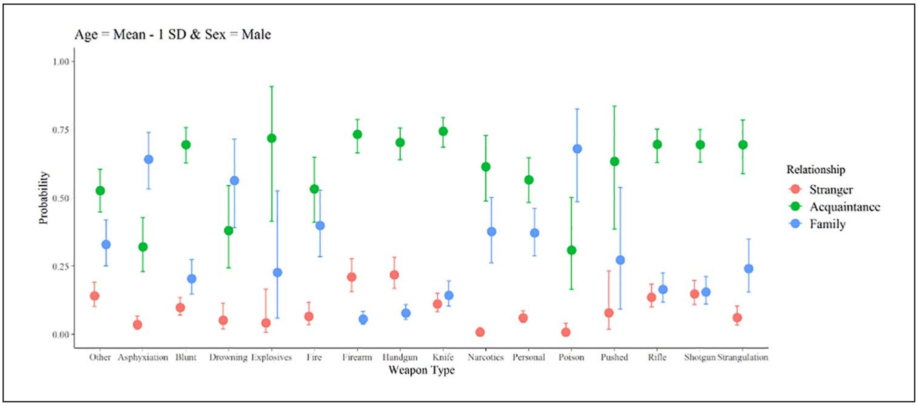

Figure 2. Parameter estimates from the interaction between victims' age, victims' sex, and weapon type. These conditional posterior distributions are for younger (–1 *SD*) males. The category labeled firearm refers to "firearm—type not stated".

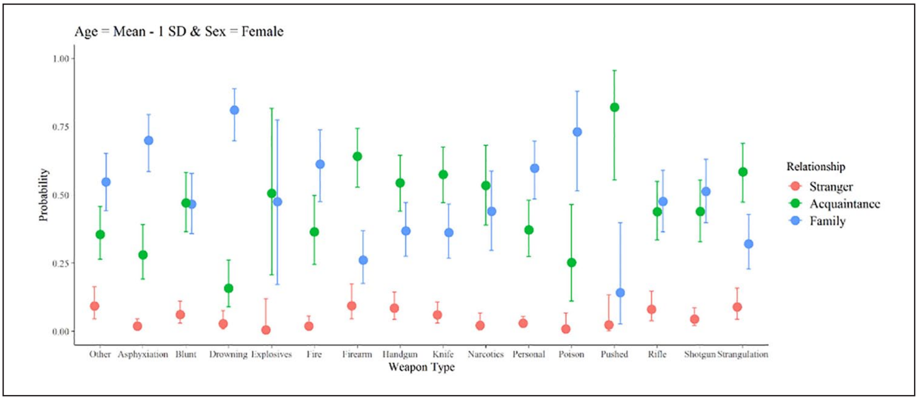

Figure 3. Parameter estimates from the interaction between victims' age, victims' sex, and weapon type. These conditional posterior distributions are for younger (–1 *SD*) females. The category labeled firearm refers to "firearm—type not stated".

weapon types. However, with average age females, with nearly all weapon types, the perpetrator is even more likely to be a family member. For example, with younger females, when handguns or knives were used, the probability was higher that the perpetrator was an acquaintance, but for average age females, family members were most probable.

Older males and females. For older male victims, the perpetrator was still most likely to be an acquaintance, across most weapon types (Figure 6). However, when a handgun was used, a stranger was just as likely to be the perpetrator as an acquaintance.

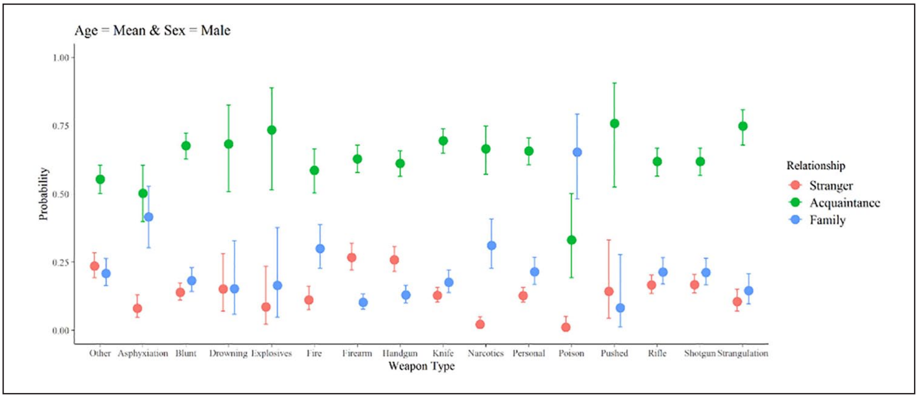

Figure 4. Parameter estimates from the interaction between victims' age, victims' sex, and weapon type. These conditional posterior distributions are for average age males. The category labeled firearm refers to "firearm—type not stated".

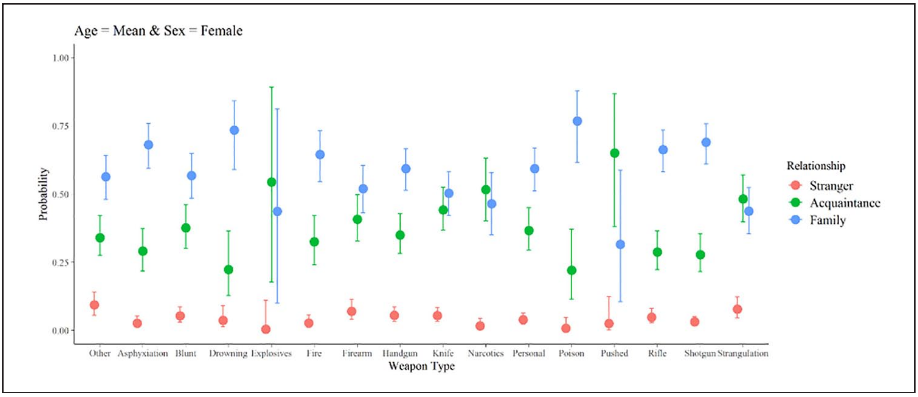

Figure 5. Parameter estimates from the interaction between victims' age, victims' sex, and weapon type. These conditional posterior distributions are for average age females. The category labeled firearm refers to "firearm—type not stated".

Comparing older male victims, to average age male victims, the probability in general, tended to increase that the perpetrator was a stranger. However, that still depended on weapon type, with older males having a low probability to be killed by a stranger when poison was the weapon. For older female victims, the weapon effects tended to be similar to average age female victims; strangers were unlikely perpetrators and family members were the most likely perpetrator, for most weapon types (Figure 7). In cases of narcotics however, the perpetrator was most likely to be an acquaintance. In cases of strangulation the perpetrator was as likely to be a family member as an acquaintance.

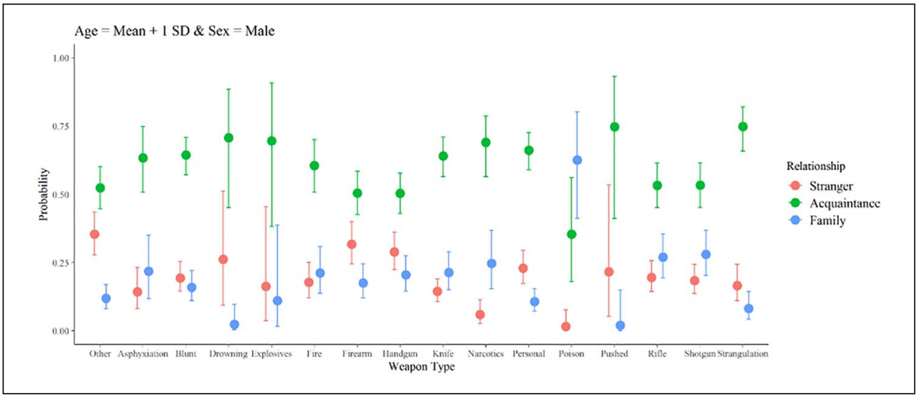

Figure 6. Parameter estimates from the interaction between victims' age, victims' sex, and weapon type. These conditional posterior distributions are for older (+1 *SD*) males. The category labeled firearm refers to "firearm—type not stated".

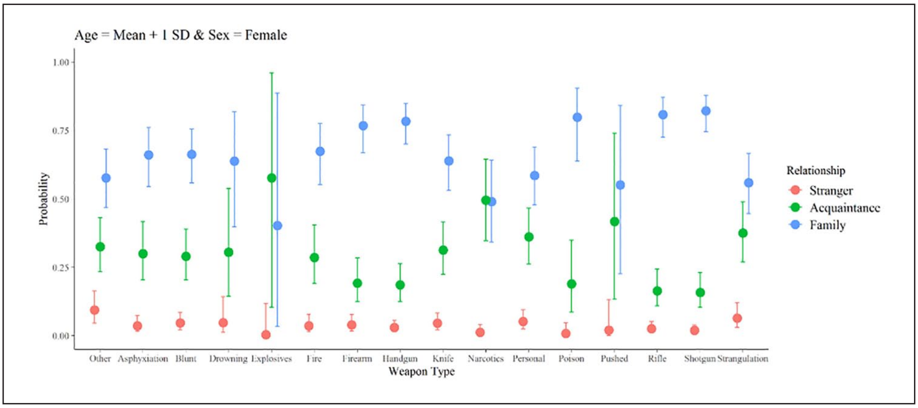

Figure 7. Parameter estimates from the interaction between victims' age, victims' sex, and weapon type. These conditional posterior distributions are for older (+1 *SD*) females. The category labeled firearm refers to "firearm—type not stated".

Discussion

The purpose of this research was to use a large data set and apply Bayesian multi-level modeling, to build a model that uses weapon type used in the homicide, and other victim information, to predict the relationship between victim and perpetrator. In doing so, we also hoped to resolve some inconsistencies in past research. The majority of the effects of weapon type on relationship type, depended on the victim's age and sex. Interestingly, when poison was used, the most probable perpetrator was consistently a family member, regardless of the victim being a male or female. It is unclear why this effect occurs. It could be that in cases where the murder is committed by a family member for financial gain, there is motivation to obscure that the death was caused by another person. Alternatively, poison generally requires some level of access to the victim, which would be easiest to exploit for family members. In other words, the relationship could be driven either by the nature of the relationship between victim and perpetrator, or the nature of the weapon itself (Chan & Beauregard, 2016). Regardless, we would expect this effect to replicate in other countries, as there are many available sources of poison in homes around the world. Firearms effects on the other hand, could vary more, considering the wide availability of firearms in the United States compared to other countries, and some of the factors that impact firearm deaths (Olson & Maltz, 2001; Pelletier & Pizarro, 2019).

In relation to firearms, we found evidence relating to handguns that was consistent with past research (e.g., Fox & Allen, 2014; Fox & Zawitz, 1999; Reynolds et al., 2019). In past research, handguns have been found to be more associated with strangers, particularly when the victim is a male, than expected by chance. Here, we found that handguns were one of the few weapon types, where the second most likely perpetrator was a stranger, particularly for younger and average age males. Thus, we have converging evidence that there is a relationship between handgun use and the perpetrator being a stranger. However, here, the strengths of our data analytic strategy are apparent.

While it is true that the relationship between handguns and strangers being the perpetrator, stand out. It must also be considered that in no case were handguns predicting the most probable perpetrator being a stranger. For males, when handguns were used, the most probable perpetrator was always an acquaintance, and for females, sometimes the most probable perpetrator was an acquaintance and other times a family member, depending on the victim's age. The plots of the conditional posterior distributions make that clear. However, that nuance is not well captured in the correspondence analysis in Fox and Allen (2014) and the multinomial regression in Reynolds et al. (2019). This highlights a major advantage of Bayesian analysis; the results are easier to understand.

While it is most critical that the analyst themselves understand the results, when others cannot understand them, the impact is necessarily lessened. Those who might make most use of these results, actual homicide investigators, need to understand them. Concepts in the frequentist framework are notoriously misunderstood (Goodman, 2008). An advantage of Bayesian modeling is their interpretation is straightforward, partly stemming from a more intuitive definition of probability. Here we can see one of the substantial contributions of this work.

Another advantage of our approach is the use of multilevel modeling. Past research on weapon type and relationship type has tended not to account for more complex multilevel structures that might be present in the data. Considering that the states in the US, each have different weapon laws which could affect if that weapon is used in a homicide, and who chooses that weapon, it is important to account for these effects. We found that a model with varying intercepts over counties and states, but not varying slopes, improved model predictions, given the added complexity. Future research should therefore model these effects when present in the data.

Limitations and Future Directions

Limitations include that we could only examine single victim-single perpetrator homicides and that we were not able to model all relationship categories. As in previous research (e.g., Fox & Allen, 2014), due partly to the logistical issues in coding multiple victim or multiple offender cases in the SHRs (see Maltz, 1999) these cases were excluded. As cases in which there are multiple victims or perpetrators represent a substantial portion of all homicides, it would be useful in the future to include them and examine how they may differ from single-victim/single-perpetrator homicides and this could be modeled in a Bayesian multilevel analysis.

Our results are also limited due to collapsing the outcome variable, relationship type, into three categories (family, acquaintance, and stranger). Categories are often reduced in these datasets, partly due to potential confounding with the acquaintance category, because victims could fit into multiple subgroups (e.g., friend and employee), and it is not always clear how investigators select one versus the other. While our categorization of relationship type is consistent with past research (e.g., Fox & Allen, 2014) the SHRs contain 28 relationship categories, and it would be advantageous to model as many as possible. For example, while it is true that when poison is used, the most probable perpetrator is a family member, a family member could mean husband, wife, mother, father, sister, brother, common-law husband, and common-law wife. Furthermore, while common-law partners are considered family members, boyfriends and girlfriends are considered acquaintances. We expect common-law partners and boyfriends/girlfriends to be similar, thus it is not clear if treating these as different categories is optimal. In the future, we could attempt to resolve any issues with using acquaintance as a category, and instead model each relationship separately. The issue with this using Bayesian analysis, would likely be that a model with 28 relationship categories and 16 to 17 weapon types is exceptionally complex and it is unlikely that such a model could be fit given the current computational power available. Another potential issue with modeling each relationship separately, is that there will be very few or even no cases for particular combinations of relationships and weapon types making inference hard without incorporating substantial prior information.

Lastly a limitation is the data itself. The vast majority of cases are officially reported homicides through the SHR. However, the cases are from arrests rather than convictions. Furthermore, even if they were from convictions, some of the individuals convicted might actually be innocent. Additionally, because the cases in the SHR are pooled from all over the United States, there can be inconsistencies in reporting and some categories might have higher disagreement. Pizarro and Zeoli (2013) found in fact that victim offender relationships are one category with high disagreement. By using data from the MAP, that contains homicides not reported to the FBI, we addressed one limitation of SHR data, which is that it contains only reported crime. However, the MAP data does not address the disagreement in victim-perpetrator relationships or the other issues with SHR data. As more high-quality data is gathered, models can be updated and improved.

Conclusions

While there is existing research on using weapon type to predict relationship type, we have extended these results by going beyond mere associations and engaged in model building, included more weapon types, examined multilevel structures often present in these datasets but rarely analyzed, used a more comprehensive homicide dataset that includes unreported homicides, and applied Bayesian statistics which have a more intuitive interpretation. On this latter point, this is particularly informative for homicide investigators, who need to know what information at the crime scene, like weapon type, tells us about the probable perpetrator. Much work remains undone, including expanding the types of relationship types that we can model, adding variables to the model (e.g., victim's socioeconomic status), and examining how these results could be used in real cases. Nonetheless, applying Bayesian multilevel models to these homicide data has been highly informative, should be used to address these future areas of research as the models can be scaled up to include these effects, and thus represents substantial contributions to this growing literature.

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