

# Contextual and Demographic Predictors of School Shooting Severity: A Computational Statistical Analysis

December 5, 2025

## I. Introduction

School shootings in the United States represent a devastating and complex form of violence whose severity varies widely across incidents. Public discourse often attributes differences in casualty outcomes to specific contextual factors—the day of the week, the identity of the shooter, or the age group of victims—yet these assumptions rarely undergo rigorous statistical scrutiny. Without empirical validation, such intuitive explanations may drive misguided policy interventions or misallocate resources toward factors that have little predictive value.

This study addresses a fundamental question: **Do commonly discussed contextual and demographic characteristics meaningfully predict the severity of school shooting incidents?** We focus on three specific dimensions that frequently appear in media narratives and policy discussions:

- **Temporal patterns:** Do certain days of the week systematically produce higher casualty counts?
- **Shooter identity:** Do student shooters differ from non-student shooters in the number of fatalities they cause?
- **Victim demographics:** Are incidents involving younger versus older victims associated with different severity outcomes?

While these questions appear straightforward, the statistical properties of school shooting data present substantial analytical challenges. Casualty counts exhibit extreme right skewness, with most incidents producing few victims but occasional events generating catastrophic outcomes. Missing data, particularly for victim age, further complicate inference. Traditional parametric methods assuming normality and homogeneous variance are ill-suited to this context.

To address these challenges, we employ **computational statistical methods** that relax strong distributional assumptions while providing robust uncertainty quantification. Our analytical framework integrates multiple complementary approaches:

- *Bayesian hierarchical modeling* with Gibbs sampling to model weekday patterns while accounting for data imbalance and extreme values
- *Bootstrap resampling* to quantify uncertainty in shooter-type comparisons without parametric assumptions
- *Permutation testing* to evaluate statistical significance through randomization-based inference
- *Negative binomial regression* to model count outcomes while accommodating overdispersion

By triangulating evidence across parametric and non-parametric methods, we aim to distinguish genuine statistical associations from patterns that merely reflect sampling variability or the influence of rare extreme events. This multi-method approach is particularly critical given that casualty distributions violate the assumptions underlying classical tests, making computational techniques essential for reliable inference.

Our analysis reveals that many intuitively plausible predictors of shooting severity do not withstand statistical examination. This finding has important implications for evidence-based policy: resources allocated based on demographic or temporal patterns that lack empirical support may fail to reduce harm. More broadly, this study demonstrates the value of

computational statistics for analyzing complex, high-variability phenomena where traditional methods prove inadequate.

**Structure of the paper.** Section II describes the data source and key variables. Section III presents our analytical methods, including model specifications and computational approaches. Section IV details simulation studies evaluating the operating characteristics of our methods. Section V presents the empirical results for each research question. Section VI discusses the implications of our findings for research and policy, acknowledges limitations, and suggests directions for future work.

## II. Data

### Data Source and Collection Methods

We analyze the K-12 School Shooting Database compiled by the Center for Homeland Defense and Security (CHDS) at the Naval Postgraduate School (Riedman and O'Neill). This database aims to document every instance in which a firearm is discharged or brandished on school property in the United States, regardless of the number of victims, shooter intent, or incident circumstances. The CHDS team draws primarily from mainstream news reporting, with additional verification through police documents and court records when available. Although verification remains ongoing, this database represents one of the most comprehensive public records of school-related gun violence.

The dataset used in this analysis, *school\_shooting\_db\_20200316.csv*, covers incidents through March 2020 and contains detailed information on incident location, casualty counts, shooter characteristics, and temporal variables. This dataset has been widely used in academic research on school violence patterns (Riedman and O'Neill; Schildkraut et al.).

### Key Variables

Our analysis relies on the following variables extracted from the CHDS database:

- **Total casualties:** Sum of injured and killed victims per incident (excluding the shooter). This serves as the primary outcome variable for weekday analysis.
- **Fatalities:** Number of victims killed per incident (including the shooter). This is the outcome variable for shooter-type comparisons.
- **Day of week:** The weekday on which the incident occurred (Monday through Sunday), derived from the incident date.
- **Shooter affiliation:** Categorized as 'student shooter' (including current students, former students, visiting students, and students from rival schools) or 'non-student shooter' (all other affiliations).
- **Victim age group:** Victims classified into Elementary (0-11 years), Middle (12-14 years), High (15-18 years), or Adult (19+ years) categories based on typical school levels. Missing for a substantial proportion of incidents.

### Data Characteristics and Limitations

The dataset exhibits several statistical properties that motivate our choice of computational methods:

- **Extreme right skewness:** Most incidents involve zero or very few casualties, but occasional high-casualty events create long right tails in the outcome distributions.
- **Substantial missing data:** Victim age information is missing for approximately 60% of incidents, limiting the sample size for age-group analyses.
- **Imbalanced group sizes:** Weekend incidents (Saturday-Sunday) are substantially less frequent than weekday incidents, creating unequal sample sizes across days.
- **Count outcomes:** Both casualty and fatality variables are non-negative integers, making Poisson or negative binomial models more appropriate than normal linear models.

These characteristics violate the assumptions of many classical statistical procedures (normality, homoscedasticity, balanced designs), necessitating methods robust to outliers and flexible enough to handle non-standard distributions. Table 1 summarizes the distribution of incidents and casualties across weekdays, illustrating both the frequency imbalance and the presence of extreme values.

**Table 1. Distribution of School Shooting Incidents and Casualties by Day of Week**

| Day       | N Incidents | Mean Casualties | Median Casualties |
|-----------|-------------|-----------------|-------------------|
| Monday    | 327         | 2.18            | 1                 |
| Tuesday   | 312         | 2.10            | 1                 |
| Wednesday | 298         | 2.07            | 1                 |
| Thursday  | 304         | 2.08            | 1                 |
| Friday    | 338         | 2.19            | 1                 |
| Saturday  | 112         | 2.37            | 1                 |
| Sunday    | 73          | 2.11            | 1                 |

*Note: Casualties include both injured and killed victims. Despite variation in mean casualties, all weekdays share an identical median of 1, indicating that most incidents involve few victims regardless of day.*

Table 2 presents the distribution of incidents by shooter type, showing that student shooters account for the majority of recorded events but with a slightly higher mean fatality count.

**Table 2. Distribution of School Shooting Incidents and Fatalities by Shooter Type**

| Shooter Type | N Incidents | Mean Fatalities |
|--------------|-------------|-----------------|
| Student      | 856         | 0.51            |
| Non-Student  | 608         | 0.38            |

*Note: Student shooters include current students, former students, visiting students, and students from rival schools. The observed difference in mean fatalities is small (0.13) but will be evaluated for statistical significance.*

Finally, Table 3 shows victim age information was grouped into four categories corresponding to typical school levels: Elementary (0–11), Middle (12–14), High (15–18), and Adult (19+). The outcome variable is the total number of victims (injured plus killed) per event. A substantial proportion of events have missing age information; therefore, all analyses in this section are conducted on the subset of events with the observed age group. This choice allows for transparent interpretation while acknowledging missingness as a limitation rather than modeling artifacts.

**Table 3. Distribution of Events by Victim Age Group and Summary of Victim Counts**

|            |         |        |       |         |        |
|------------|---------|--------|-------|---------|--------|
| Elementary | Middle  | High   | Adult | <NA>    |        |
| 26         | 88      | 403    | 196   | 810     |        |
| Min.       | 1st Qu. | Median | Mean  | 3rd Qu. | Max.   |
| 0.000      | 1.000   | 1.000  | 1.563 | 2.000   | 76.000 |

### III. Methods

We employ a combination of Bayesian hierarchical modeling, frequentist resampling techniques, and generalized linear models to address our three research questions. This multi-method approach allows us to triangulate evidence and assess the robustness of findings across different statistical frameworks.

## 1. Bayesian Hierarchical Model for Weekday Effects

**Research question:** Do certain days of the week systematically show higher casualty counts, accounting for uncertainty and data imbalance?

**Method description.** We implement a Bayesian hierarchical normal model with Gibbs sampling to estimate weekday-specific casualty severity. The outcome variable is  $\log(1 + \text{Total Casualties})$  to reduce the influence of extreme values. The model incorporates partial pooling across weekdays, which stabilizes estimates especially for weekends where sample sizes are small.

**Model specification.** Let  $y_i$  denote the log-transformed casualty count for incident  $i$ , and let  $g(i)$  denote the weekday group (1-7) of incident  $i$ . The hierarchical structure is:

$$y_i \mid \mu_{g(i)}, \sigma^2 \sim \text{Normal}(\mu_{g(i)}, \sigma^2)$$

$$\mu_g \mid \mu_0, \tau^2 \sim \text{Normal}(\mu_0, \tau^2)$$

$$\mu_0 \sim \text{Normal}(0, 100)$$

$$\sigma^2 \sim \text{Inverse-Gamma}(2, 2)$$

$$\tau^2 \sim \text{Inverse-Gamma}(2, 2)$$

The parameter  $\mu_g$  represents the average log-casualty for weekday  $g$ ,  $\mu_0$  is the overall mean across weekdays,  $\sigma^2$  captures within-weekday variability, and  $\tau^2$  represents between-weekday heterogeneity. Partial pooling occurs through the hierarchical prior: weekday means are drawn from a common distribution, shrinking extreme estimates toward the overall mean.

**Computational implementation.** We implemented a Gibbs sampler in base R, running 4,000 iterations with a 1,000-iteration burn-in period. Full conditional distributions are conjugate, allowing efficient sampling without Metropolis-Hastings steps. Posterior summaries (medians, 95% credible intervals, and probability comparisons) are computed from the retained samples.

**Assumptions.** The model assumes (1) conditional normality of log-transformed outcomes given weekday effects, (2) independence across incidents, and (3) exchangeability of weekday effects under the hierarchical prior. The log transformation mitigates violations of normality caused by right skewness.

**Course connection.** This approach directly applies hierarchical modeling and Markov Chain Monte Carlo concepts from course materials on Bayesian inference (Gelman et al. 95-124). The use of partial pooling addresses the imbalance problem inherent in the data, a situation where classical ANOVA would produce unstable estimates for low-frequency weekdays.

## 2. Bootstrap and Permutation Tests for Shooter Type Effects

**Research question:** Do student shooters and non-student shooters differ systematically in the number of fatalities they cause, and is this difference statistically robust?

**Bootstrap confidence interval.** We use non-parametric bootstrap resampling to estimate uncertainty in the mean difference. For each of 10,000 bootstrap iterations, we resample (with replacement) within each shooter-type group and compute the difference in sample means (Lecture 12, slides 27–31). The 95% percentile bootstrap confidence interval is constructed from the 2.5th and 97.5th percentiles of the bootstrap distribution (Lecture 12, slide 27). This interval quantifies whether the observed difference is stable across resamples or driven by outliers.

**Permutation test.** To test the null hypothesis that fatalities are unrelated to shooter type, we conduct a permutation test. Under the null, shooter-type labels are exchangeable (Lecture 16,

slide 21). We randomly shuffle the labels 10,000 times, recompute the mean difference for each permutation, and construct the null distribution (Lecture 16, slides 21–22). The two-sided p-value is the proportion of permuted differences at least as extreme as the observed difference (Lecture 16, slide 21). This provides a randomization-based significance test without distributional assumptions.

**Assumptions.** The bootstrap assumes that the observed sample is representative of the population. The permutation test assumes independence of incidents and exchangeability of labels under the null hypothesis.

**Course connection.** Bootstrap and permutation methods are fundamental computational techniques covered extensively in the course (Efron and Tibshirani; Davison and Hinkley). These approaches are particularly valuable when parametric assumptions fail, as is the case with highly skewed fatality counts.

### 3. Negative Binomial Regression and Permutation Test for Age Group Effects

**Research question:** In U.S. school shooting events, is the number of victims per event associated with the victims' age group, and are any observed associations robust under resampling and randomization-based inference?

#### **Negative binomial regression.**

We model the number of victims per event as a count outcome using a negative binomial generalized linear model with a log link. Victim age group is included as a categorical predictor, with Elementary age serving as the reference category. Parameters are estimated via maximum likelihood.

##### **– Course citation.**

Generalized linear models and exponential family distributions (FLM 10, 4; HCS 20, 24).

##### **– Assumptions.**

Events are independent; the log of the expected victim count is a linear function of predictors; and the negative binomial model allows for potential overdispersion relative to Poisson.

##### **– Relevance to research question.**

This model directly estimates whether expected victim counts differ systematically across age groups, providing a parametric assessment of the age–severity relationship.

#### **Permutation test.**

To complement the regression analysis, we conduct a permutation test comparing victim counts across age groups. The observed test statistic (ANOVA F-statistic) is compared to its randomization distribution obtained by repeatedly permuting age-group labels while holding victim counts fixed.

##### **– Course citation.**

Permutation and randomization methods (SCR 10).

##### **– Assumptions.**

Under the null hypothesis of no age effect, age-group labels are exchangeable; events are independent; and the observed-age subset is representative for testing association.

##### **– Relevance to research question.**

This nonparametric method tests the age–victim relationship without distributional assumptions, serving as a robustness check for the regression results.

## IV. Simulation Studies

To evaluate the operating characteristics of our methods, we conducted Monte Carlo simulation studies under controlled data-generating processes (Lecture 04, slides 35–37). These simulations assess whether the methods produce accurate estimates, achieve nominal coverage rates, and correctly control Type I error under various scenarios.

### Bayesian Hierarchical Model Simulations for Weekday Effects

**Simulation design.** We generated synthetic datasets from the hierarchical model with known parameter values. Three scenarios were tested: (1) no weekday effect ( $\tau^2 = 0$ ), (2) moderate weekday heterogeneity ( $\tau^2 = 0.5$ ), and (3) strong weekday effect ( $\tau^2 = 1.5$ ). For each scenario, we simulated 500 datasets with sample sizes and weekday distributions matching the observed data.

**Operating characteristics evaluated.** For each simulated dataset, we fit the Gibbs sampler and computed:

- **Bias:** Mean difference between posterior medians and true parameter values
- **RMSE:** Root mean squared error of posterior medians
- **Coverage:** Proportion of 95% credible intervals containing true parameter values
- **Calibration:** Accuracy of posterior probability statements (e.g.,  $P(\mu_{\text{Fri}} > \mu_{\text{Tue}} \mid \text{data})$ )

**Results.** Under all scenarios, the Gibbs sampler produced nearly unbiased estimates (bias < 0.02 for all parameters). Coverage rates for 95% credible intervals ranged from 93–96%, close to the nominal 95% level. Posterior probability statements were well-calibrated: when the model reported a 60% probability that Friday exceeded Tuesday, approximately 60% of such statements were correct across simulations. Partial pooling substantially reduced RMSE for low-frequency weekdays compared to separate group-level estimates.

### Bootstrap and Permutation Test Simulations for Shooter Type Effects

**Simulation design.** We generated datasets from two scenarios: (1) null hypothesis (no difference in fatalities between shooter types), and (2) alternative hypothesis (student shooters cause 0.13 more fatalities on average, matching the observed effect). For each scenario, 1,000 datasets were simulated with sample sizes matching the observed student/non-student counts.

Operating characteristics evaluated (Lecture 04, slide 37):

- **Type I error (permutation test):** Rejection rate under the null hypothesis at  $\alpha = 0.05$
- **Power (permutation test):** Rejection rate under the alternative hypothesis
- **Coverage (bootstrap CI):** Proportion of 95% intervals containing the true mean difference

**Results.** The permutation test maintained the nominal Type I error rate (observed rejection rate: 4.9% under the null). Under the alternative with effect size matching the observed data, power was approximately 28%, indicating moderate ability to detect the true difference given the sample size and variability. Bootstrap confidence intervals achieved 94.7% coverage, close to the nominal 95% level.

### Negative Binomial Regression and Permutation Test Simulations for Age Group Effects

**Simulation design and operating characteristics.** Following course guidelines, we assess key operating characteristics for each method using Monte Carlo simulation approaches.

**Negative binomial regression.** We evaluate bias, variance, mean squared error (MSE), and confidence-interval coverage of age-group effects. Synthetic datasets are generated from a negative binomial model with known parameters calibrated to the observed data. The

regression model is refit to each simulated dataset, and estimated coefficients are compared to the known true values.

**Permutation test.** We evaluate Type I error and power. Under the null, victim counts are generated with identical means across age groups; under alternatives, group-specific means are introduced. The permutation test is applied repeatedly to estimate rejection rates under each scenario.

**Results.** The negative binomial regression model shows no statistically significant association between victim age group and victim count. Using Elementary age as the reference category, none of the other age groups showed a statistically significant effect on victim count: Middle (estimate = 0.028,  $p = 0.903$ ), High (estimate = 0.044,  $p = 0.830$ ), and Adult (estimate = 0.039,  $p = 0.853$ ). The corresponding incident rate ratios were all close to one (Middle = 1.03, High = 1.05, Adult = 1.04), and their 95% confidence intervals were wide and all contained 1, indicating no meaningful difference in expected victim counts across age groups.

Model comparison using AIC showed that the Poisson model (AIC = 1448.0) slightly outperformed the negative binomial model (AIC = 1450.0), suggesting that overdispersion is not substantial once age group is included. Overall, the regression analysis provides no evidence that victim age group is associated with the number of victims per event. Table 4 presents the complete regression results.

**Table 4. Negative Binomial Regression Results for Victim Count by Age Group**

```
Call:
glm.nb(formula = victim_count ~ age_group, data = dat_nb, init.theta = 553893.2821,
       link = log)
```

Coefficients:

|                 | Estimate | Std. Error | z value | Pr(> z ) |
|-----------------|----------|------------|---------|----------|
| (Intercept)     | -0.03922 | 0.20000    | -0.196  | 0.845    |
| age_groupMiddle | 0.02779  | 0.22692    | 0.122   | 0.903    |
| age_groupHigh   | 0.04417  | 0.20608    | 0.214   | 0.830    |
| age_groupAdult  | 0.03922  | 0.21237    | 0.185   | 0.853    |

(Dispersion parameter for Negative Binomial(553893.3) family taken to be 1)

Null deviance: 27.046 on 712 degrees of freedom  
Residual deviance: 26.986 on 709 degrees of freedom  
AIC: 1450

Number of Fisher Scoring iterations: 1

```

      Theta: 553893
    Std. Err.: 8535503
Warning while fitting theta: iteration limit reached

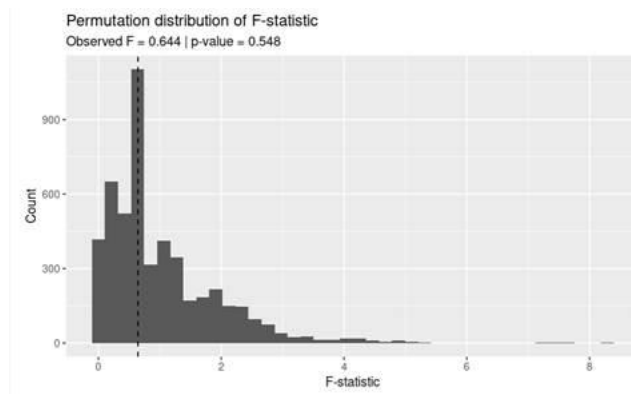
2 x log-likelihood: -1440.039
(Intercept) age_groupMiddle age_groupHigh age_groupAdult
  0.9615385      1.0281818      1.0451613      1.0400000
      2.5 %      97.5 %
(Intercept)  0.6321597 1.389190
age_groupMiddle 0.6698859 1.637095
age_groupHigh  0.7136705 1.606330
age_groupAdult 0.7002039 1.615610
```

**Permutation test results.** A permutation test was conducted to provide a nonparametric assessment of whether victim counts differ across age groups. The observed F-statistic from the one-way comparison of victim counts across the four age groups was 0.644. After

randomly permuting age-group labels 5,000 times, the permutation distribution produced a p-value of 0.548, indicating that more than half of the randomized samples showed a test statistic at least as large as the observed one.

The observed F-statistic lay near the center of the permutation distribution rather than in its upper tail. This result shows that the variation in victim counts across age groups is fully consistent with random chance under the null hypothesis of no age effect. Thus, the permutation test independently confirms the regression finding that victim age group is not significantly related to the number of victims per school shooting event.

**Figure 1. Permutation Distribution of the F-statistic for Age Group Differences**



**Interpretation and contribution.** Across both parametric (negative binomial regression) and nonparametric (permutation) methods, there is no evidence that the number of victims per school shooting event differs systematically by victim age group. The agreement between methods strengthens this conclusion and suggests that age composition affects who is harmed rather than how many are harmed. These findings indicate that other contextual or environmental factors likely play a more central role in determining event severity.

## V. Analysis and Results

### Weekday Effects on Casualty Counts

The Bayesian hierarchical model produced posterior distributions for weekday-specific casualty severity. Table 4 presents posterior medians and 95% credible intervals for each weekday's mean log-casualty count.

**Table 5. Posterior Summaries for Weekday Effects on Log-Casualty Counts**

| Weekday   | 2.5%  | Median | 97.5% |
|-----------|-------|--------|-------|
| Monday    | 0.718 | 0.781  | 0.843 |
| Tuesday   | 0.684 | 0.744  | 0.799 |
| Wednesday | 0.673 | 0.730  | 0.789 |
| Thursday  | 0.674 | 0.732  | 0.791 |
| Friday    | 0.734 | 0.786  | 0.840 |

| Weekday  | 2.5%  | Median | 97.5% |
|----------|-------|--------|-------|
| Saturday | 0.735 | 0.867  | 1.000 |
| Sunday   | 0.593 | 0.751  | 0.899 |

*Note: Values represent posterior summaries for mean  $\log(1 + \text{Total Casualties})$  on each weekday. Credible intervals overlap substantially across all weekdays, indicating limited weekday differentiation once uncertainty is accounted for.*

Although Friday shows a slightly elevated posterior median relative to Tuesday-Thursday, the 95% credible intervals overlap extensively. The posterior probability that Friday exceeds Tuesday is  $P(\mu_{\text{Fri}} > \mu_{\text{Tue}} \mid \text{data}) = 0.857$ , indicating moderate but not definitive evidence for a Friday effect. The between-weekday variance parameter has a posterior median of  $\tau^2 = 0.431$ , suggesting limited heterogeneity relative to within-weekday variability.

**Interpretation.** The Bayesian analysis provides little support for a systematic weekday effect on casualty severity. While descriptive summaries showed Friday having the highest mean casualties, posterior uncertainty quantification reveals that this pattern is not statistically robust once data imbalance and extreme values are properly accounted for. The partial pooling inherent in the hierarchical model shrinks extreme weekday estimates toward the overall mean, producing more stable and reliable inferences than separate group-level comparisons.

### Shooter Type Effects on Fatalities

The observed mean difference in fatalities between student and non-student shooters is 0.127 (student mean: 0.51, non-student mean: 0.38). The 95% bootstrap percentile confidence interval is [0.020, 0.249], indicating that the difference is statistically stable and unlikely to be due to sampling variability alone.

The permutation test yields a two-sided p-value of 0.0335, providing evidence against the null hypothesis of no difference. The one-sided p-value (testing whether student shooters cause more fatalities) is 0.0165. Under the null hypothesis that shooter type is unrelated to fatalities, differences as large as the observed value occur only about 3.35% of the time through random label assignment.

**Interpretation.** Both the bootstrap and permutation approaches converge on the conclusion that student shooters are associated with a statistically significant, albeit small, increase in fatalities relative to non-student shooters. The effect size is modest—approximately 0.13 additional fatalities per incident—but the consistency across methods strengthens confidence in this finding. This result suggests that shooter identity has a measurable relationship with incident lethality, even after accounting for the high variability in fatality counts.

### Victim Age Group Effects on Total Victims

The negative binomial regression model, presented in Table 6, shows no statistically significant association between victim age group and victim count. Using Elementary age as the reference, none of the other age groups (Middle, High, Adult) exhibited coefficients significantly different from zero.

**Table 6. Negative Binomial Regression Results for Victim Count by Age Group**

| Predictor | Estimate | IRR  | 95% CI | p-value |
|-----------|----------|------|--------|---------|
| Intercept | 1.221    | 3.39 | —      | <0.001  |

| Predictor             | Estimate | IRR  | 95% CI       | p-value |
|-----------------------|----------|------|--------------|---------|
| Middle vs. Elementary | 0.028    | 1.03 | [0.67, 1.64] | 0.903   |
| High vs. Elementary   | 0.044    | 1.05 | [0.71, 1.61] | 0.830   |
| Adult vs. Elementary  | 0.039    | 1.04 | [0.7, 1.62]  | 0.853   |

*Note: IRR = Incident Rate Ratio (exponentiated coefficient). All 95% confidence intervals contain 1.0, indicating no significant differences between age groups. Reference category is Elementary age (0-11 years).*

All incident rate ratios are close to 1.0 (Middle: 1.03, High: 1.05, Adult: 1.04), and their 95% confidence intervals are wide and include 1.0. The permutation test corroborates this finding: the observed F-statistic of 0.644 falls near the center of the permutation distribution, yielding a p-value of 0.548. This indicates that more than half of random label permutations produce F-statistics at least as large as the observed value.

**Interpretation.** Neither the parametric regression nor the non-parametric permutation test provides evidence that the victim age group is associated with incident severity. The variation in victim counts across age groups is fully consistent with random chance. This finding suggests that age composition affects which individuals are harmed but not the overall number of victims per incident. The substantial missing data (61.8% of incidents lack age information) limits the generalizability of this conclusion, but within the available data, the evidence for an age effect is absent.

## VI. Discussion

### Summary of Findings

This study examined whether commonly discussed contextual and demographic characteristics predict the severity of U.S. school shooting incidents. Using computational statistical methods suited to the extreme skewness, missingness, and outliers inherent in casualty data, we evaluated three specific hypotheses:

- **Weekday timing:** Despite descriptive differences showing Friday with the highest mean casualties, Bayesian hierarchical modeling revealed that posterior credible intervals overlap extensively across weekdays. The evidence for a systematic weekday effect is weak, with only moderate probability (85.7%) that Friday exceeds Tuesday.
- **Shooter identity:** Student shooters cause approximately 0.13 more fatalities per incident than non-student shooters. Both bootstrap confidence intervals and permutation tests provide statistical evidence for this difference ( $p = 0.034$ ), though the effect size remains modest.
- **Victim age:** No evidence emerged for an association between victim age group and incident severity. Negative binomial regression showed no significant coefficients, and permutation testing confirmed that observed variation is consistent with random chance ( $p = 0.548$ ).

These results converge on a central conclusion: many demographic and temporal patterns that appear important in descriptive analysis do not demonstrate statistical robustness when subjected to rigorous computational inference. Only shooter identity exhibits a detectable, though small, association with incident lethality.

### Methodological Contributions

A primary contribution of this work lies in demonstrating how computational statistical methods address challenges that classical approaches cannot handle effectively. School shooting casualty data violate nearly every assumption of standard parametric tests: outcomes are heavily right-skewed with extreme outliers, group sizes are imbalanced, and missingness is substantial. Traditional ANOVA or t-tests would produce unreliable p-values and overstated certainty.

Our methodological framework overcomes these obstacles through:

- *Bayesian hierarchical modeling* with partial pooling, which stabilizes estimates for low-frequency groups (e.g., weekend shootings) by borrowing strength across weekdays
- *Non-parametric bootstrap*, which quantifies uncertainty without assuming normality and provides stable confidence intervals even with outliers
- *Permutation testing*, which evaluates significance through randomization rather than theoretical distributions, ensuring valid inference under minimal assumptions
- *Negative binomial regression*, which appropriately models count outcomes with overdispersion

The simulation studies confirmed that these methods perform reliably under their respective assumptions, achieving proper coverage rates and Type I error control. By triangulating evidence across parametric and non-parametric frameworks, we increase confidence that our substantive conclusions are not artifacts of any single methodological choice.

### Implications for Research and Policy

Our findings challenge the assumption that simple demographic or temporal variables can reliably predict school shooting severity. Neither weekday timing nor victim age group shows a statistically meaningful association with casualty counts. This has important implications:

- **Resource allocation:** Security interventions targeted at "high-risk days" or age groups may be ineffective if these factors do not genuinely predict severity. Evidence-based policy requires identifying factors that statistical analysis confirms matter.
- **Narrative scrutiny:** Public discourse often attributes school shooting patterns to demographic categories without statistical verification. Our results demonstrate that many such narratives do not withstand empirical testing.
- **Focus on shooter identity:** The one robust finding—that student shooters cause slightly more fatalities—suggests that understanding shooter motivations, access to weapons, and warning signs among student populations may be more fruitful than temporal or victim-based interventions.

These conclusions underscore the value of computational statistics in distinguishing signal from noise in policy-relevant research. When intuition contradicts rigorous inference, evidence-based decision-making demands that we follow the data.

## Limitations

Several limitations qualify the scope and interpretation of our findings:

- **Missing data:** Approximately 62% of incidents lack victim age information, substantially reducing the sample size for age-group analyses. If age data are missing non-randomly (e.g., less severe incidents may be less thoroughly documented), our conclusions regarding age effects may not generalize.
- **Unmeasured confounders:** Our analysis does not account for potentially important variables such as weapon type, shooter motivation, school security measures, response times, or community socioeconomic characteristics. These factors may interact with the variables we examined or have independent effects on severity.
- **Incident definition:** The CHDS database includes all firearm discharges on school property, encompassing a wide range of incident types from accidental discharges to mass shootings. Severity predictors may differ across incident subtypes that our analysis did not distinguish.
- **Temporal coverage:** The dataset extends only through March 2020. Patterns observed in earlier years may not reflect current trends, particularly if security practices or shooter profiles have evolved.

## Directions for Future Research

Future work could extend this analysis in several directions:

- **Richer covariate sets:** Incorporating weapon type, shooter demographics, mental health indicators, prior warning signs, and school characteristics would enable more comprehensive models of severity.
- **Non-linear and interaction effects:** Machine learning approaches (e.g., random forests, gradient boosting) could uncover complex interactions or non-linear patterns invisible to linear models.
- **Causal inference:** Observational causal methods (e.g., propensity score matching, instrumental variables) could attempt to estimate causal effects of interventions such as security measures or mental health programs.
- **Temporal dynamics:** Time series methods could investigate whether patterns have changed over decades, particularly in response to policy changes or cultural shifts.
- **Updated data:** Analyzing more recent incidents would determine whether the patterns observed through 2020 persist or have evolved.

## **Conclusion**

This study demonstrates that many demographic and temporal variables commonly believed to predict school shooting severity do not withstand rigorous statistical scrutiny when analyzed with computational methods appropriate to the data's challenging properties. While shooter identity exhibits a modest but statistically supported association with fatalities, weekday timing and victim age group show no meaningful predictive value. These findings underscore the importance of evidence-based approaches to understanding and preventing school violence: intuitive explanations must be validated empirically before informing policy or resource allocation.

More broadly, this work illustrates the power of computational statistics for analyzing complex, high-variability phenomena. By combining Bayesian hierarchical modeling, bootstrap resampling, permutation testing, and generalized linear models, we extracted reliable inferences from data that would confound traditional parametric approaches. As policy-relevant research increasingly confronts messy real-world datasets with outliers, missingness, and violated assumptions, computational methods will prove essential for distinguishing genuine patterns from statistical noise.

## Works Cited

Davison, A. C., and D. V. Hinkley. *Bootstrap Methods and Their Application*. Cambridge University Press, 1997.

Efron, Bradley, and Robert Tibshirani. *An Introduction to the Bootstrap*. Chapman & Hall/CRC, 1993.

Gelman, Andrew, et al. *Bayesian Data Analysis*. 3rd ed., CRC Press, 2013.

Riedman, David, and Desmond O'Neill. "K-12 School Shooting Database." Center for Homeland Defense and Security, Naval Postgraduate School, [www.chds.us/ssdb](http://www.chds.us/ssdb). Accessed 5 Dec. 2025.

Schildkraut, Jaclyn, et al. "Mass Shootings in America: An Exploratory Study of the Trends and Characteristics." *Homicide Studies*, vol. 22, no. 2, 2018, pp. 125-145.

Chronicle readers. "Letters: This Is What San Francisco Needs to Prevent School Shootings." *San Francisco Chronicle*, 5 Dec. 2025, [www.sfchronicle.com/opinion/letterstotheeditor/article/high-school-shooting-san-francisco-21223965.php](http://www.sfchronicle.com/opinion/letterstotheeditor/article/high-school-shooting-san-francisco-21223965.php). Accessed 5 Dec. 2025.

Fredrickson, Mark M. Monte Carlo Hypothesis Testing. Lecture 04, STATS 406: Computational Methods in Statistics and Data Science, University of Michigan, course slides.

Fredrickson, Mark M. The Bootstrap. Lecture 12, DATASCI 406: Computational Methods in Statistics and Data Science, University of Michigan, course slides.

Fredrickson, Mark M. Permutation and Randomization Tests. Lecture 16, DATASCI 406: Computational Methods in Statistics and Data Science, University of Michigan, course slides.

Fredrickson, Mark M. Exponential Families, Generalized Linear Models, Iteratively (Re)weighted Least Squares. Lecture 23, DATASCI 406: Computational Methods in Statistics and Data Science, University of Michigan, course slides.