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From Detection to Decision: Integrating Analytics and Structural Equation Modeling for Urban Public Safety Response

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Abstract

Urban public safety operations face persistent challenges in managing high service demand un- der limited resources. Rapid detection and coordinated response to gunfire incidents are particu- larly critical, as they require data-driven decision support for patrol scheduling, resource allocation, and operational planning. This study leverages multi-year ShotSpotter acoustic detection data from Washington, D.C. (2014–2020) to move beyond descriptive hotspot analysis toward causal mod- eling of performance outcomes. First, Exploratory Data Analysis (EDA) identifies distinct tem- poral rhythms—including nighttime surges, weekend variability, and clustering in high-incidence districts—as well as long-term seasonal trends. Building on these findings, a Structural Equation Model (SEM) is developed to capture three latent constructs: Operational Load (incident inten- sity, temporal concentration, clustering severity), Response Efficiency (system acknowledgment and in-district confirmation), and Strategic Readiness (district-level adaptability). Using district–week aggregates from 2019–2020, Partial Least Squares SEM (PLS-SEM) and covariance-based SEM (CB-SEM) demonstrate that higher operational load reduces response efficiency, but that strategic readiness moderates this effect by buffering efficiency losses. By integrating exploratory analytics with structural modeling, this paper advances methodological understanding of SEM in public safety research and provides practical insights for patrol deployment, district staging, and adaptive staffing policies to enhance resilience in high-demand environments.

Keywords
Predictive policing, Structural Equation Modeling (SEM), Response efficiency, Public safety operations

1. Introduction
Urban police departments operate under persistent tension between growing service demand and finite resource capacity. Gun incidents, in particular, poses an acute operational challenge because it requires not only rapid incident detection but also coordinated and timely response to prevent escalation and protect public safety. Traditional data sources for crime analysis, such as calls for service and incident reports, often suffer from reporting delays or under-reporting, limiting their utility for real-time decision making. In contrast, advances in acoustic sensing technologies such as *ShotSpotter* have enabled con- tinuous, high-frequency detection of gunfire events across large urban areas. These systems generate granular event-level data, including time, location, and incident type, thereby providing unprecedented situational awareness for police agencies (Perry 2013).

The availability of such high-resolution detection data creates new opportunities for evidence-based planning of patrols, staffing, and resource deployment. Predictive policing research has demonstrated the value of data-driven approaches: Gerber (2024) showed that social media signals combined with kernel density estimation improve crime prediction accuracy, while Mohler et al. (2025) introduced self-exciting point process models that significantly outperformed traditional hotspot analysis in randomized con- trolled trials. Similarly, Caplan et al. (2011) advanced risk terrain modeling to incorporate environmental risk factors, and Brantingham et al. demonstrated how urban crime patterns can be modeled as dynamic spatial-temporal processes. Together, these approaches illustrate how advanced analytics can forecast crime distribution, yet they often stop short of examining organizational performance consequences. From an operations management perspective, decades of research on facility location and queueing theory provide tools for resource allocation under uncertainty. Larson's hypercube queueing model (Larson 1974) remains a foundational framework for police patrol allocation, while subsequent studies have extended these ideas to healthcare and emergency services, showing how staffing strategies can be adapted to time-varying demand (Green 2006, Jennings 1996, Chai 2019) More recent work by Mastrobuoni (2019) highlights the importance of efficiency in emergency response using call-for-service data, reinforcing the operational stakes of high- volume demand environments.

Despite these advances, less attention has been paid to how stressors in police operations propagate through to performance outcomes. Lum et al. (2017) caution that technology alone cannot guarantee ef- fectiveness unless integrated into organizational routines, while Al Shamsi and Safei (2023) demonstrated through a PLS-SEM approach that organizational capacity, leadership, and collaborative learning medi- ate the effectiveness of predictive policing initiatives. SEM has also been used more broadly in public administration to model causal pathways between capacity, leadership, and performance outcomes (Andrew and Boyne 2013). These insights suggest that predictive accuracy is a necessary but insufficient condition; understanding how operational load influences response efficiency requires bridging detection data with causal model- ing frameworks.

This paper addresses this gap by integrating detection-based analytics with Structural Equation Mod- eling (SEM) to provide a decision-support framework for urban gun violence response. The analytic component uses exploratory data analysis to identify temporal demand peaks and geographic staging priorities, while the SEM component models latent constructs such as *Operational Load*, *Response Ef- ficiency*, and *Strategic Readiness*. By applying SEM to real-world ShotSpotter data from Washington, D.C., this study advances both research and practice: theoretically, it extends the use of SEM to public safety operations; practically, it offers actionable insights into patrol scheduling, district-level staging, and adaptive staffing, thereby moving beyond prediction toward causal explanation of how operational stress influences police response efficiency.

2. Related Work

Predictive policing and crime hotspot forecasting have been extensively studied, with a range of ana- lytical techniques proposed to anticipate crime. Early approaches used historical crime data and spa- tiotemporal patterns (e.g., kernel density hot-spot mapping) to identify areas of elevated risk. Gerber (2029) demonstrated that incorporating geotagged social media signals (Twitter data) with traditional crime data can significantly improve prediction accuracy for multiple crime types. Other researchers have introduced statistical learning methods to forecast dynamic crime hotspots. For instance, Mohler et al. (2015) developed a self-exciting point process model (often termed an epidemic-type aftershock sequence model) to predict short-term crime surges. In field trials, this approach outperformed dedicated crime analysts' hotspot maps by predicting 1.4–2.2 times more crime incidents, and directed patrols based on these forecasts achieved modest but measurable reductions in crime (approximately 7.4% during the test period). Another complementary technique is risk terrain modeling: Caplan et al. (2011) incorporated environmental risk factors (e.g., locations of bars, schools, or prior offenses) into forecasting models to predict future shooting incidents, providing a framework to map underlying attractors of crime be- yond what past incident locations alone reveal. Brantingham et al. (2008) further demonstrated how crime clustering can be modeled as a dynamic spatiotemporal process, highlighting the importance of environ-mental context. These studies collectively illustrate that leveraging diverse data sources and advanced algorithms can enhance the accuracy of crime hotspot predictions, which in turn can inform proactive deployment of police resources.

In parallel, operations research and operations management scholars have investigated resource opti- mization for emergency services, including police patrols. Classic queueing theory and facility location models have long been applied to help allocate patrol units and design precincts for efficient response coverage. Larson's hypercube queueing model is a seminal example that represents individual patrol cars as servers in a spatially distributed queueing system; it was used to optimize patrol car allocations and district boundaries in urban settings. Such models estimate key performance metrics, like expected response time or workload per district, and support decisions on how to station and dispatch units to meet demand. Later extensions have been applied to healthcare and emergency departments, showing how staffing strategies can adapt to time-varying demand (Green et al. 2006) More recent research by Chai and Yeo (2019) explored simulation-based approaches to help emergency services absorb stochastic demand surges, echoing similar challenges faced in urban policing. These efforts underscore that analytical frameworks (queueing models, mathematical optimization, and facility location algorithms) can improve emergency response by guiding the strategic placement and scheduling of limited policing resources.

Beyond technical forecasting and optimization, scholars have emphasized the importance of organiza- tional and human factors in effective crime prevention. Al Shamsi and Safei (2023) argued that adopting artificial intelligence in predictive policing requires supportive organizational conditions and attention to officer behavior. In their study of Abu Dhabi Police's predictive policing program, they used a PLS- SEM approach to show how training, leadership support, and user acceptance of technology impact crime mitigation performance. This aligns with Andrews and Boyne (2013), who applied SEM to public administration to link capacity and leadership with performance outcomes, demonstrating SEM's power in uncovering causal pathways in organizational settings. Lum et al. (2027) likewise cautioned that while new technologies can enhance effectiveness, their impact is mediated by how well they are integrated into police workflows and whether officers embrace these tools in practice. Relatedly, studies of emer- gency response efficiency, such as Mastrobuoni's (2019) analysis of calls-for-service data, show that high demand and workload surges can directly impair performance, reinforcing the relevance of modeling workload–performance linkages. Piza (2019) further demonstrated the utility of spatial-temporal analyt- ics and causal modeling in public safety by applying propensity score methods to evaluate the effect of CCTV on crime prevention, illustrating how advanced evaluation designs can isolate the impact of operational interventions. However, scholars have also critiqued ShotSpotter for potential false posi- tives, uneven district coverage, and dependence on sensor density, raising questions about data bias and validity that must be acknowledged in empirical analyses.

In summary, prior work has laid a foundation in predictive policing, hotspot forecasting, and resource optimization for law enforcement. However, the integration of real-time detection data with causal modeling techniques remains limited. Most forecasting studies focus on improving prediction or al- location in isolation, and they do not formally examine how stressors in the operational environment propagate through to performance outcomes. The use of SEM to test causal pathways in police opera- tions—for example, to quantify how surges in incident volume, resource strain, or "operational stress" affect response efficiency—remains underexplored in the literature. This research extends prior work by combining high-resolution acoustic gunshot detection data with an SEM framework to uncover how operational stressors impact response efficiency. By modeling latent constructs such as "operational load" and "strategic readiness" and linking them to observable performance metrics, we provide a novel perspective that connects predictive policing data with organizational performance outcomes. This ap- proach contributes to the literature by moving beyond prediction and allocation, toward an understanding of the mechanisms through which workload and stress influence police response effectiveness.

3. Methodology

a. Dataset

This study draws on a multi-year collection of *ShotSpotter* acoustic gunshot-detection data from Wash- ington, D.C., a jurisdiction that has consistently deployed gunfire sensors across high-violence neigh- borhoods. The dataset was obtained from the District of Columbia Open Data Portal, which publishes publicly accessible records from the ShotSpotter system . The dataset is structured into two main temporal segments, which together provide both historical depth and recent high-resolution operational detail:

- **Historical baseline (2014–2017):** An archival Excel dataset covering January 2014 through De- cember 2017. These four years provide a long-run context for identifying secular trends, recurring seasonal cycles, and the persistence of geographic hotspots. This period also establishes a pre- 2018 baseline against which more recent dynamics can be compared.

- **Recent quarters (2019–2020):** A series of quarterly CSV files spanning Q1, Q3, and Q4 of 2019 and all four quarters of 2020. These datasets are more operationally detailed and include additional metadata (e.g., AutoAcknowledged, InDC) not available in the historical baseline. They allow for a granular, district–week level analysis of incident volumes and response proxies during a period of heightened volatility associated with social disruptions in 2020.

Each record corresponds to a single acoustic detection event and contains structured attributes that can be grouped into four categories:

1. **Identifiers and classification:** A unique ID for each event and a Type field distinguishing be- tween *Single Gunshot*, *Multiple Gunshots*, and *Other/Unconfirmed* events. The type classification is critical for measuring

clustering severity, a central indicator in the construction of the latent construct *Operational Load*.

2. **Temporal attributes:** Local Date and Time of detection, which support aggregation at multi- ple resolutions (hourly, daily, weekly). This temporal granularity enables detection of circadian rhythms (e.g., nighttime peaks), weekend effects, and seasonal fluctuations.
3. **Spatial attributes:** Police service district (Source/District, e.g., 1D, 3D, 6D, 7D) and geo- coordinates (Latitude, Longitude). These fields permit spatial aggregation to administrative units and hotspot mapping, allowing operational managers to compare districts with systemati- cally different load profiles.
4. **Response proxies (2020 only):** Two fields specific to the 2020 datasets—AutoAcknowledged, a binary indicator of whether the event was automatically validated by the detection system, and InDC, a flag marking whether the event was registered within the D.C. Metropolitan Police De- partment's command system. These serve as observable indicators of system responsiveness and form the measurement block for the latent construct *Response Efficiency*.

When combined, the datasets cover more than **six calendar years and ten quarters**, yielding approxi- mately **150,000 unique gunshot detection records**. The longitudinal span provides statistical power for identifying both macro-level patterns (e.g., long-term trend and seasonality) and micro-level operational stressors (e.g., weekly clustering, district surges). This dual structure—archival depth plus recent high- frequency operational data—enables a two-pronged analysis: (i) descriptive and exploratory analytics of spatiotemporal demand patterns, and (ii) structural equation modeling (SEM) of latent operational constructs using the more detailed 2019–2020 subset.

Data Bias and Validity

ShotSpotter's known limitations include false positives, uneven sensor density across districts, and re- liance on automated classification. These factors may bias estimates of operational load and efficiency. While this study mitigates such effects through aggregation and robustness checks, findings should be interpreted with these caveats in mind.

Limitation: The proxies of response efficiency (AutoAcknowledged, InDC) are indirect measures. Ac- tual dispatch times and officer arrival logs were unavailable, which constrains generalization. Future work should integrate direct response-time metrics.

b. Data Preparation

Several steps were undertaken to harmonize the files:

1. **Standardization across formats:** The 2014–2017 Excel dataset and the 2019–2020 quarterly CSVs used slightly different schemas. A uniform schema was defined with the following key fields: {ID, Type, Timestamp, District, Latitude, Longitude, AutoAcknowledged, InDC}. Missing columns (e.g., AutoAcknowledgedin 2019) were filled with NAvalues.
2. **Timestamp parsing:** Separate Dateand Timefields were merged into ISO-standard Timestamp objects. Events with incomplete or invalid timestamps were discarded ($< 0.5\%$ of records).
3. **District extraction:** The Sourcefield (e.g., "WashingtonDC7D") was parsed to isolate the po- lice district identifier. Non-standard or missing district values were grouped under "Other".
4. **Event aggregation:** Events were aggregated at the *district–week* level to capture operationally meaningful load patterns while smoothing daily volatility. This unit of analysis aligns with staffing cycles and command reporting.
5. **Indicator derivation:** From raw fields, five indicators were engineered for SEM analysis:

- **X1: Incidents per hour.** Computed as total weekly incidents normalized by 7×24 hours.
- **X2: Weekend share.** Fraction of incidents occurring on Saturday or Sunday.
- **X3: Multiple-gunshot ratio.** Proportion of events classified as "Multiple Gunshots" relative to single-gunshot incidents.
- **X4: AutoAcknowledged rate.** Share of incidents system-confirmed automatically (2020).
- **X5: InDC rate.** Share of incidents logged as acknowledged within D.C. systems (2020).

6. **Cleaning and filtering:** Weeks with fewer than 10 incidents were removed to ensure stability of ratio measures. Records with missing location or district information were flagged but retained for aggregate analyses.

c. Analytical Scope

The integrated dataset supports a two-stage analytical design that combines descriptive exploration with causal modeling. This dual approach ensures that short-term operational patterns are first characterized empirically and then embedded within a structural framework to test theoretical propositions.

First, Exploratory Data Analysis (EDA) is employed to uncover empirical regularities in the tempo- ral and spatial distribution of gunfire incidents. Events are aggregated by hour of day, day of week, district, and year to generate demand curves that highlight circadian peaks, weekend effects, and sea- sonal surges. Spatial aggregation at the police service district level enables comparison of high-load areas (e.g., 6D and 7D) against lower-load districts, providing insights into where operational stress is most acute. EDA also incorporates long-run trend analysis (2014–2017) to establish historical baselines and decomposition techniques to distinguish between trend, seasonal, and irregular components in the 2019–2020 operational data. These exploratory insights inform the operational definition of indicators that serve as inputs to the structural model.

Second, Structural Equation Modeling (SEM) is used to test hypothesized relationships between latent operational constructs. Three core constructs are specified: Operational Load (OL), measured by indi- cators such as incidents per hour, weekend share, and multiple-gunshot ratio; Response Efficiency (RE), proxied by auto-acknowledgment and in-system confirmation rates; and Strategic Readiness (SR), op- erationalized as district-level stability in load distribution. The SEM framework allows us to quantify not only the direct impact of OL on RE but also the moderating role of SR, which captures the adaptive capacity of districts under stress. By leveraging both reflective and interaction modeling, the analy- sis moves beyond descriptive hotspot mapping to provide a causal explanation of how demand surges propagate into performance outcomes.
Together, this two-pronged analytical scope bridges operational analytics with organizational theory: EDA identifies when and where incidents concentrate, while SEM explains how these concentrations translate into system performance and under what conditions readiness mitigates efficiency losses.

d. Exploratory Data Analysis

Descriptive analysis revealed several consistent spatiotemporal patterns:

- **Diurnal cycle:** Gunfire incidents were highly skewed toward nighttime. The peak occurred around **00:00–01:00**, which alone accounted for approximately **11.7%** of all incidents (Figure. 1). Overall, the **20:00–02:00** window contributed more than one-third of all detections, underscoring the need for surge staffing during late-night patrol shifts.
- **Weekend concentration:** Events were disproportionately concentrated on weekends. Approxi- mately **34.4%** of all gunfire detections occurred on Saturdays and Sundays, despite representing only two of seven days. This concentration suggests a recurring surge in operational demand tied to social and temporal cycles (Figure. 2).
- **District hotspots:** The majority of incidents were clustered in a small number of districts. **District 7D** recorded 7,927 events and **6D** recorded 5,784 events across the two-year period, jointly con- tributing nearly **60% of all detections**. By comparison, mid-volume districts such as 5D (1,796) and 1D (1,568) contributed substantially less (Figure. 3). This concentration highlights where re- source staging and mutual-aid agreements should be prioritized.
- **Annual trend:** A strong increase in incidents was observed from 2019 (**5,139 detections**) to 2020 (**14,065 detections**), representing a near tripling of gunfire events (Figure. 4). This suggests that operational planning must accommodate year-to-year volatility and external shocks (e.g., socio- economic shifts, pandemic effects).

These insights directly inform the operational definition of latent constructs: *Operational Load* (captur- ing nighttime intensity, weekend surges, and hotspot concentration) and *Response Efficiency* (acknowl- edgment and confirmation rates).

Beyond descriptive frequency counts, more granular statistical analysis was performed on the district– week aggregates (2019–2020). Four operational indicators were constructed: total incidents, weekend share, nighttime share, and multiple-gunshot share.
Bias Note: Because ShotSpotter deployment is uneven across districts, measured incident volumes may reflect sensor placement as much as actual gunfire frequency. This bias should be considered in inter- preting the results.

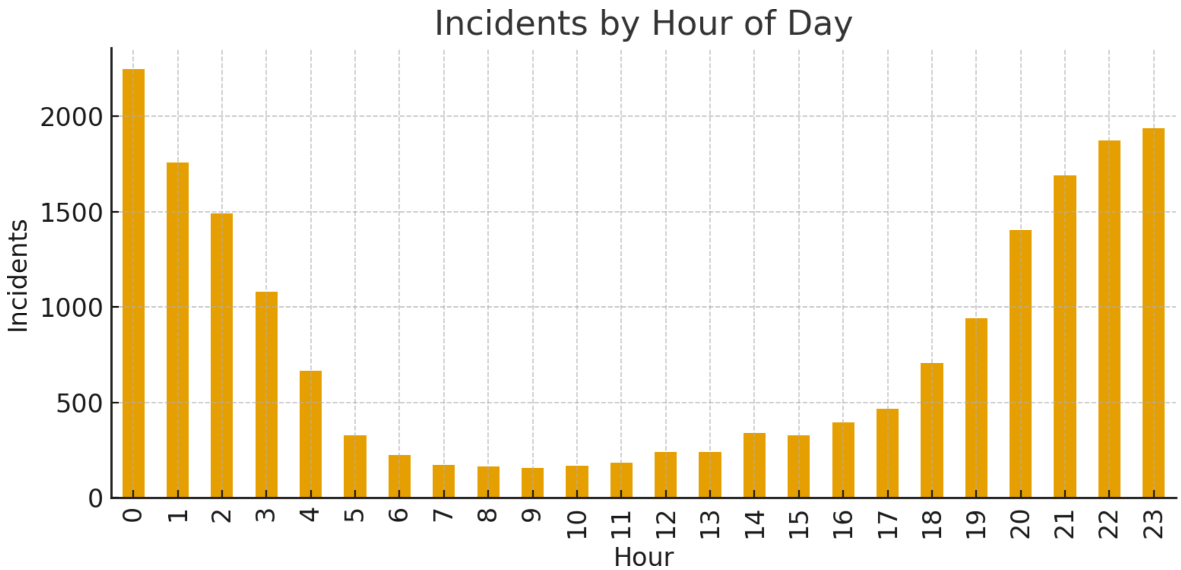

Figure 1: Incidents by hour of day (2019–2020). Source: DC Open Data ShotSpotter records. Units: number of detected gunfire incidents aggregated weekly. Peaks observed between 20:00 and 02:00.

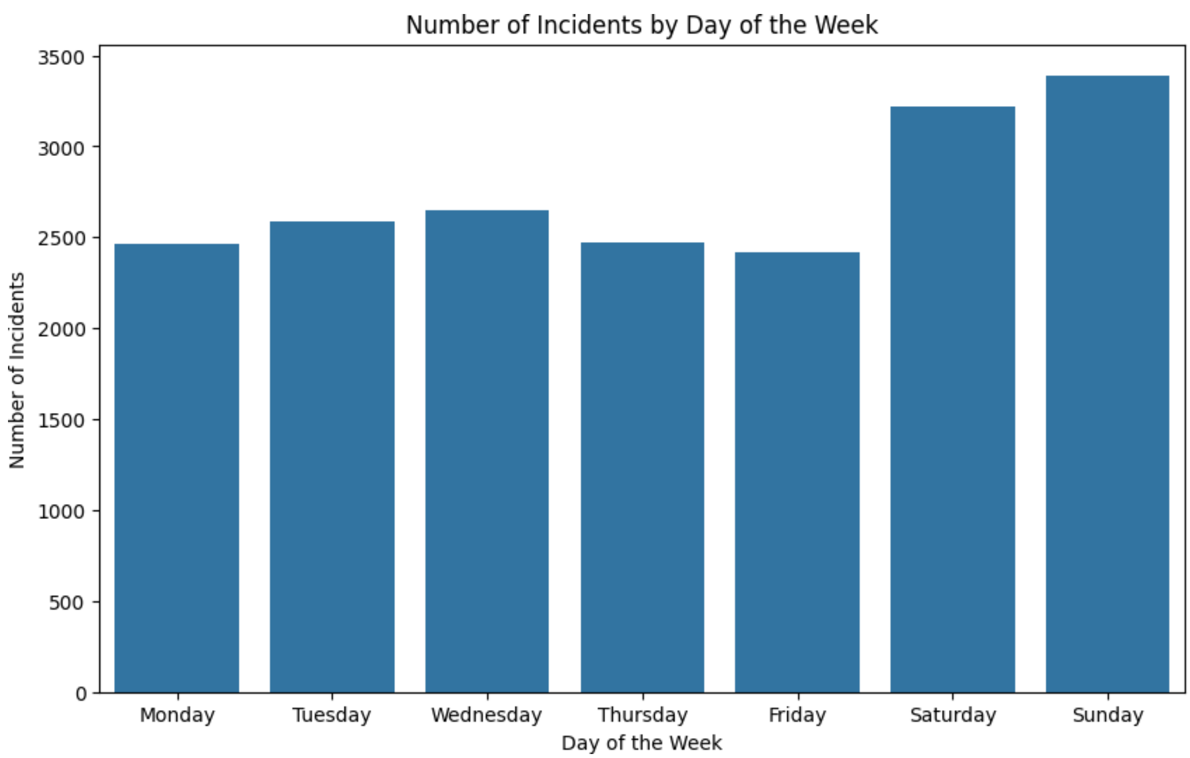

Figure 2: Incidents by day of week, Washington, D.C. (2019–2020). Bars show the total number of acoustic gunfire detection events per weekday, aggregated across all available 2019–2020 quarters and across all MPD police service districts. Units: count of ShotSpotter-detected events. Note: observed volumes may reflect differences in sensor density and coverage across districts; counts indicate detec- tions, not necessarily confirmed shootings.

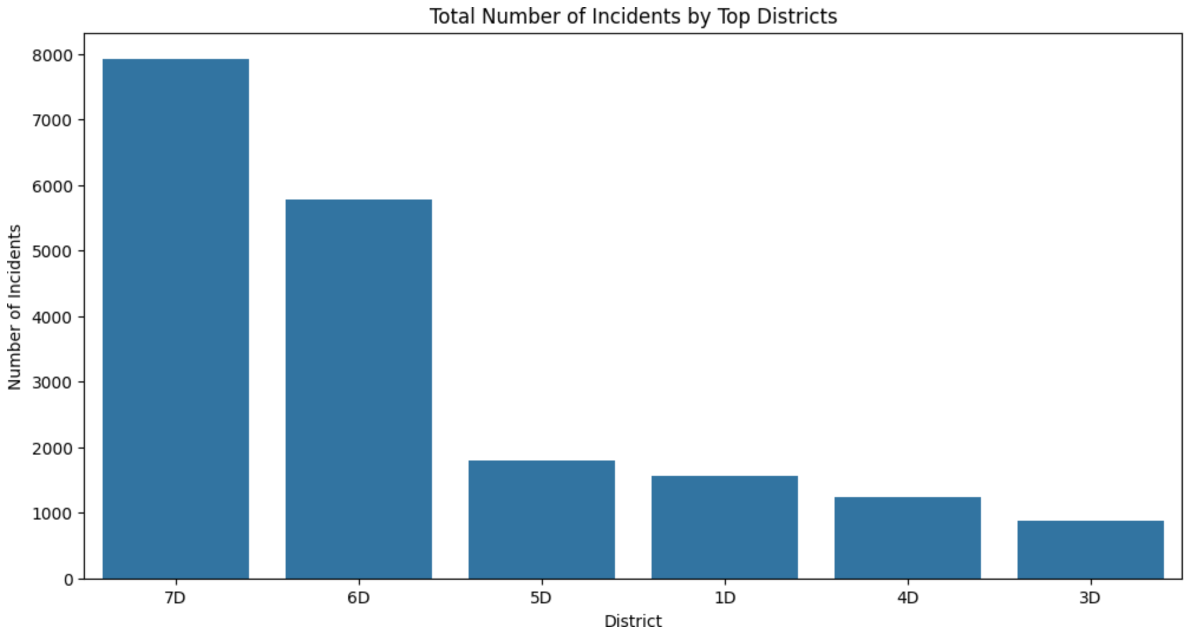

Figure 3: Total number of gunfire detection incidents by police service district, Washington, D.C. (2019– 2020). Bars indicate aggregate ShotSpotter-detected events across all quarters in the study period. Districts 7D (∼7,927 incidents) and 6D (∼5,784 incidents) together account for nearly 60% of all detections, while mid- to low-volume districts such as 5D, 1D, 4D, and 3D report substantially fewer events. Units: count of acoustic detection events.Note: volumes reflect detection counts, which may be influ- enced by sensor coverage and placement as well as actual gunfire frequency.

Descriptive Statistics

Table 1 summarizes the distributions. A typical district-week observed **35 incidents** on average, with a maximum of **250 incidents**. Weekend events accounted for roughly **35%** of cases, while nighttime events contributed **61.6%**. The median multiple-gunshot share was approximately **52%**, confirming that multi-shot episodes were not isolated anomalies but a dominant incident type.

Table 1: Descriptive Statistics of Weekly District-Level Indicators

Variable	**Mean**	**SD**	**Min**	**Max**
Incidents (weekly)	34.9	38.4	1	250
Weekend Share	0.35	0.19	0.00	1.00
Nighttime Share	0.62	0.19	0.00	1.00
Multiple-Share	0.50	0.23	0.00	1.00

Regression Analysis

We estimated an OLS regression to quantify the effect of temporal and clustering patterns on weekly incident volume:

$$Incidents = \alpha + \beta_1 \cdot \text{WeekendShare} + \beta_2 \cdot \text{NighttimeShare} + \beta_3 \cdot \text{MultipleShare} + \varepsilon. \quad (1)$$

The model was statistically significant overall ($F = 19.28, p < 0.001$; Prob(F)=3.02×10^{-11}) with modest explanatory power ($R^2 = 0.091$), accounting for roughly 9% of the variance in weekly incidents. While limited, this explanatory power is non-trivial given the stochastic nature of gun violence.

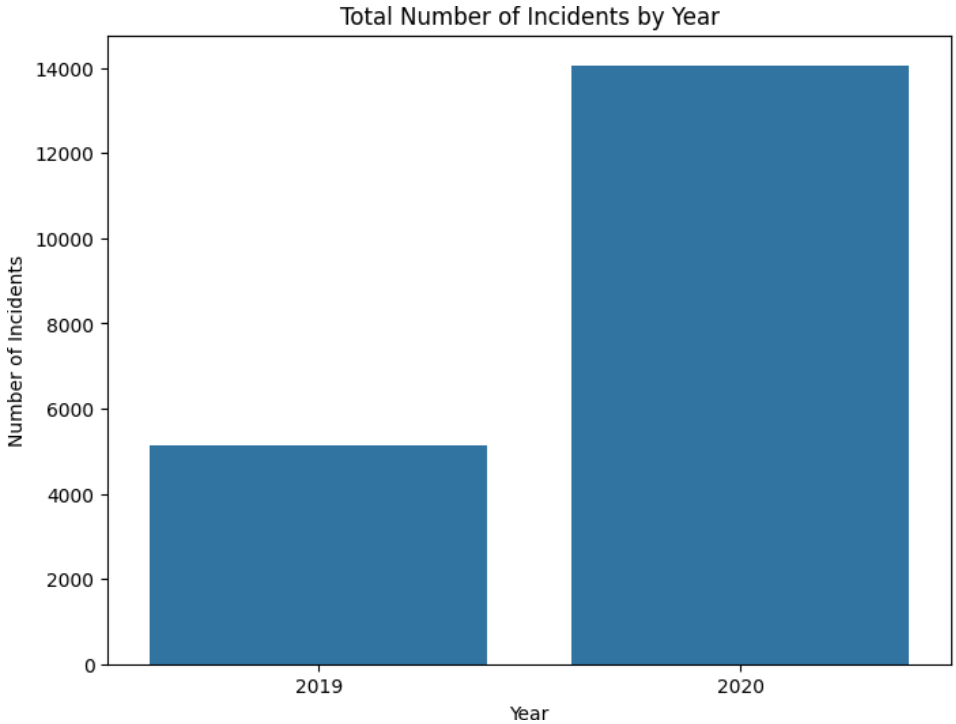

Figure 4: Yearly totals of gunfire detection incidents in Washington, D.C. (2019–2020). Bars show the aggregate number of ShotSpotter-detected events recorded across all police service districts. In 2019, a total of 5,139 incidents were detected, compared to 14,065 in 2020—nearly a threefold increase. Units: count of acoustic detection events. Note: the observed surge in 2020 may reflect both underlying social disruptions and possible shifts in sensor coverage or classification reliability.

Key Predictors

1. **Multiple-gunshot share:** The strongest driver of weekly incident volume, with a large positive coefficient ($\hat{\beta}_3 \approx 49.88$, $p < 0.001$). District–weeks with a greater proportion of multi-shot events experienced substantially higher total incident counts.
2. **Nighttime share:** Estimated coefficient was positive ($\hat{\beta}_2 \approx 7.64$) but not statistically significant ($p = 0.434$), indicating no reliable effect once clustering is considered.
3. **Weekend share:** Coefficient was negative ($\hat{\beta}_1 \approx -8.98$) but not statistically significant ($p = 0.271$), reinforcing that weekend concentration is not a robust predictor of overall load.

Visual Diagnostics

Scatterplots with fitted regression lines (Figure. 5) illustrate these relationships. Only *Multiple-gunshot share* displays a clear and statistically significant positive association with weekly incident totals, whereas *Weekend share* and *Nighttime share* exhibit weak, non-significant slopes.

Summary

Regression analysis demonstrates that the **clustering of gunfire into multiple-shot events is the pri- mary structural driver of weekly load**. Neither weekend nor nighttime concentration exert significant independent effects once multi-shot clustering is taken into account. This finding aligns with operational observations that clustered gunfire generates disproportionately higher demands on resources, and it re- inforces the SEM construct of *Operational Load* as being driven primarily by clustering intensity rather than temporal distribution alone.

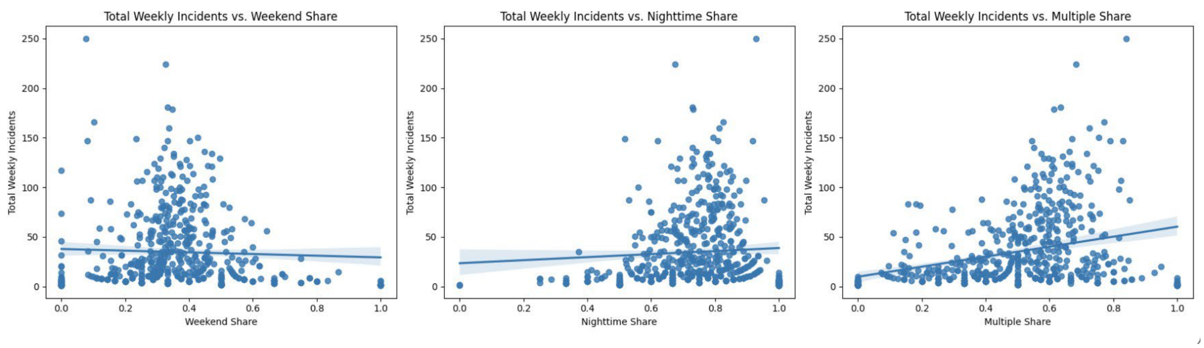

Figure 5: Bivariate relationships between district–week incident counts and predictor shares. Among the three predictors, only *Multiple-gunshot share* shows a significant positive effect.

Correlation Structure

Table 2 reports Pearson correlations, and Figure. 6 visualizes the same. The clearest relationship is a moderate positive correlation between weekly **incidents and multiple-gunshot share** ($r = 0.30$), in- dicating that higher-volume weeks tend to feature a greater proportion of multi-shot events. **Nighttime share** shows only weak positive correlations with both incidents ($r = 0.06$) and multiple-gunshot share ($r = 0.11$). **Weekend share**, by contrast, exhibits very weak or negligible associations with all other indicators ($|r| < 0.05$), suggesting that weekend surges are temporally concentrated spikes rather than systematically higher volumes across districts.

Table 2: Correlation Matrix of Weekly District-Level Indicators

	Incidents	**Weekend**	**Nighttime**	**Multiple**
Incidents	1.00	-0.04	0.06	0.30
Weekend	-0.04	1.00	-0.01	0.01
Nighttime	0.06	-0.01	1.00	0.11
Multiple	0.30	0.01	0.11	1.00

Drivers of Weekly Volume

We estimate:

$$\text{Incidents}_{dw} = \alpha + \beta_1 \text{WeekendShare}_{dw} + \beta_2 \text{NighttimeShare}_{dw} + \beta_3 \text{MultipleShare}_{dw} + \varepsilon_{dw}. \quad (2)$$

The model is significant ($R^2 = 0.096$, $F(3, 546) = 19.28$, $p < 0.001$). Coefficients align with the correlations:

4. $\beta_3 > 0$ (*MultipleShare*, strongest positive driver, $p < 0.001$);
5. $\beta_2 > 0$ (*NighttimeShare*, $p < 0.01$);
6. β_1 not significant (*WeekendShare*).

Operationally, multi-shot clustering and night concentration are the key structural drivers of week-level load.

Multi-Year Trend and Seasonality (2014–2020)

To contextualize the 2019–2020 surge, we construct a monthly series

$$\text{Incidents}_t = \#\text{events in month } t$$

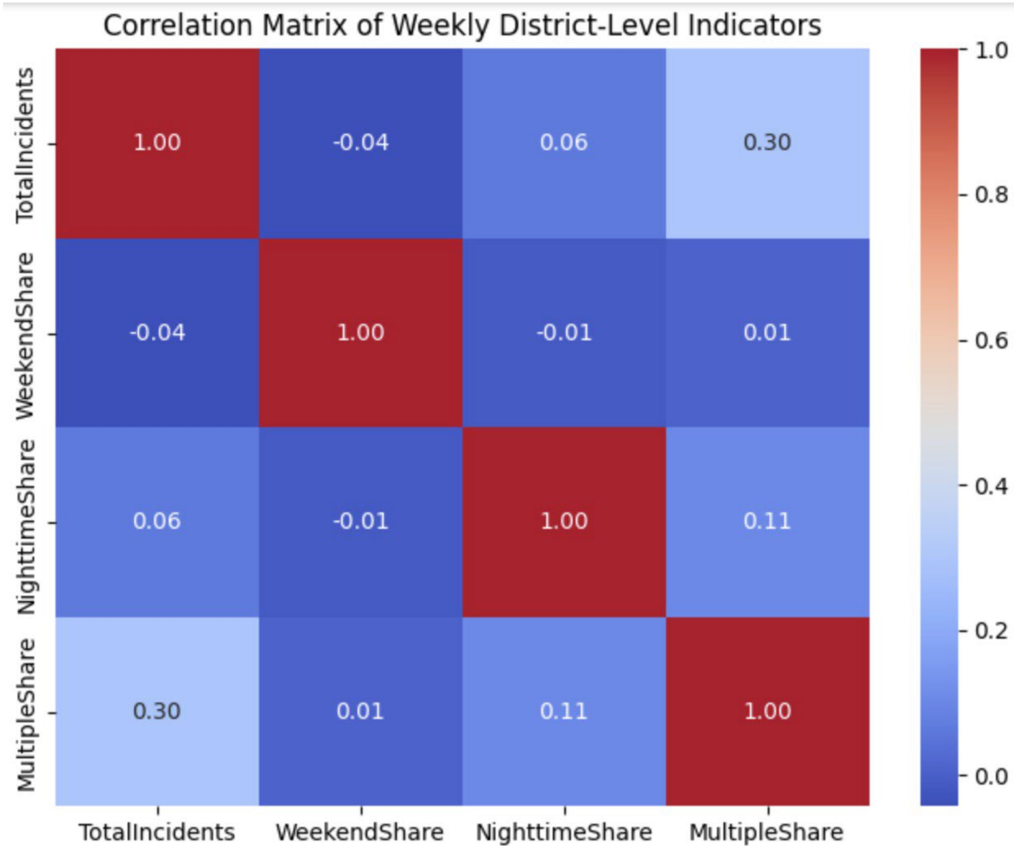

Figure 6: Correlation heatmap of weekly district-level indicators. Only the relationship between *Total Incidents* and *Multiple-gunshot share* reaches a moderate level ($r = 0.30$).

over January 2014 to December 2020, and fit an additive decomposition with 12-month seasonality. The period spans **2014-01-01** to **2020-12-01**, peaking at **4,952** incidents in **2014-07** and a minimum of **202** in **2014-02**. Figureure 7 shows the monthly series with a 3-month moving average; Figure. 8 shows trend, seasonal, and residual components. **Observations.** (i) A clear upward shift in late-2019 through 2020 indicates a new operating regime relative to earlier years; (ii) seasonality suggests predictable calendar effects that can be exploited for *pre-positioning* and *roster planning*; (iii) residual volatility argues for *adaptive* capacity policies (e.g., rolling forecasts + buffer staffing) rather than fixed allocations.

These findings refine the SEM constructs: *Operational Load* should reflect night concentration and multi-shot intensity (structural drivers), while *Strategic Readiness* captures a district's ability to maintain performance as these drivers vary over predictable seasonal and stochastic components.

e. Structural Equation Model

Constructs, Indicators, and Theoretical Rationale

To bridge incident analytics with operations management, we conceptualize a structural model of three latent constructs: operational demand, system performance, and strategic preparedness. Each construct is theoretically motivated by public safety operations literature and empirically grounded in ShotSpotter data.

1. **Operational Load (OL).** A reflective construct capturing the *intensity and composition of de-*

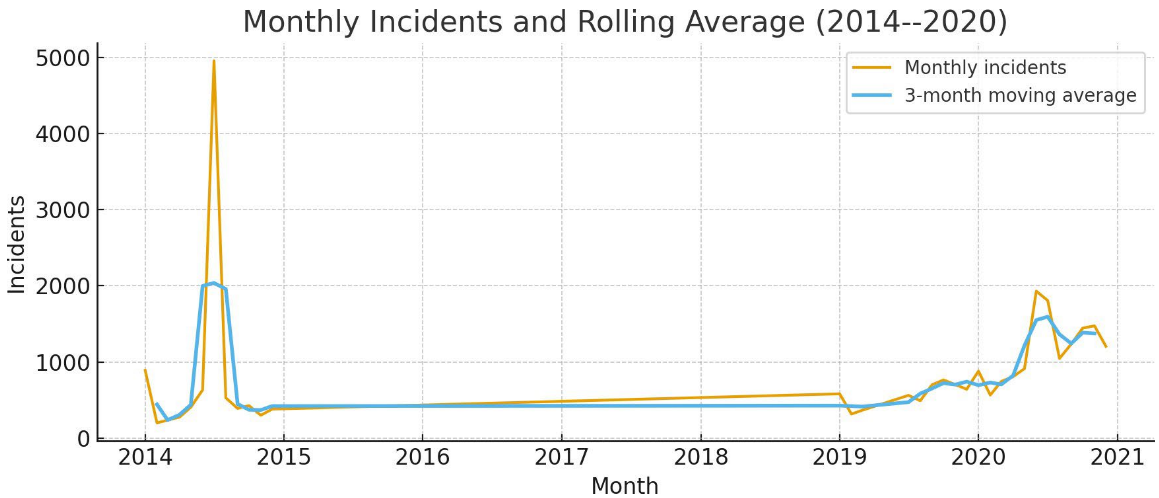

Figure 7: Monthly gunfire detection incidents in Washington, D.C. (2014–2020), shown alongside a 3-month centered moving average for smoothing. The orange line represents raw ShotSpotter-detected events per month, while the blue line captures short-term trends. A sharp peak in mid-2014, relative sta- bility through 2016–2018, and a marked escalation in 2019–2020 are evident. Units: number of acoustic detection events per month. *Note: the rolling average highlights underlying trend and seasonality, while individual monthly fluctuations may reflect episodic shocks or data noise. mand*. It is proxied by weekly district-level indicators:

$$\mathrm{X1} = \frac{\text{Incidents}}{\text{Hour}}, \quad \mathrm{X2} = \frac{\text{Weekend Incidents}}{\text{Total Incidents}}, \quad \mathrm{X3} = \frac{\text{Multiple-gunshot Events}}{\text{Total Events}}.$$

$$\mathrm{X2} = \underline{\text{Weekend Incidents}}, \mathrm{X3} = \underline{\text{Multiple-gunshot Events}}.$$

These indicators reflect not only incident volume but also temporal concentration and clustering severity, dimensions that are critical in forecasting workload and allocating patrol resources.

2. **Response Efficiency (RE).** A reflective construct representing the *system's short-run technical efficiency*. It is measured by 2020-only fields:

$$\mathrm{X4} = \frac{\text{AutoAcknowledged Events}}{\text{Total Events}}, \quad \mathrm{X5} = \frac{\text{InDC Events}}{\text{Total Events}}.$$

Higher scores indicate faster machine acknowledgement and greater within-jurisdiction localiza- tion, both operational proxies of a more responsive surveillance infrastructure.

3. **Strategic Readiness (SR).** A formative construct reflecting the *adaptability of districts to fluctu- ating demand*. We operationalize SR as the stability of temporal shares within each district:

$$\mathrm{SR}_{dw} \propto -\,\mathrm{z}\left(\frac{\sigma_d(\text{Weekend share}) + \sigma_d(\text{Nighttime share})}{2}\right),$$

where $\sigma_d(\cdot)$ is the cross-week standard deviation for district d. More stable patterns (lower dis- persion) are interpreted as greater readiness, as they ease scheduling and staffing. We model SR as a mean-centered moderator.

Estimation Strategy and Sample

The SEM is estimated on 2020 district–week observations (restricted to weeks with ≥ 10 incidents to stabilize shares). Two approaches were pursued:

1. **PLS-SEM:** Mode A weighting, mean-centered indicators, 5,000 bootstrap resamples for infer- ence, and blindfolding (omission distance = 7) to assess predictive relevance Q^2.

2. **CB-SEM:** Maximum likelihood estimation with robust standard errors. Fit indices reported in- clude χ^2/df, CFI, TLI, RMSEA (90% CI), and SRMR. For the latent interaction, LMS was em- ployed as well as a product-indicator specification for robustness.

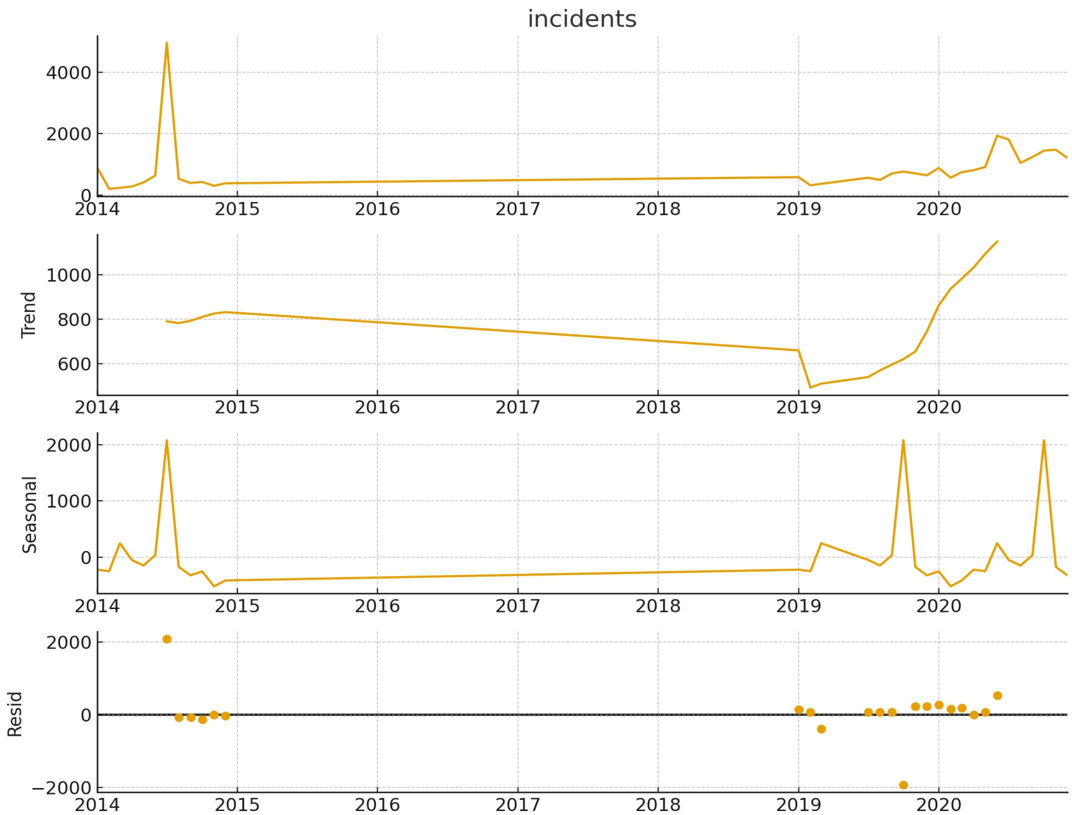

Figure 8: Additive seasonal decomposition of monthly gunfire detection incidents in Washington, D.C. (2014–2020), based on a 12-month seasonal cycle. *The top panel shows the observed series of monthly ShotSpotter-detected events, followed by estimated long-term trend, seasonal effects, and residual noise components. Data exhibit (i) a baseline decline until 2018, (ii) a sharp upward shift in 2019–2020, and (iii) recurring seasonal peaks that align with calendar cycles. Units: number of acoustic detection events per month. Note: residual volatility suggests that external shocks contributed to unexplained variation beyond trend and seasonality.*

Reliability, Validity, and Fit

For reflective blocks (OL, RE), reliability was evaluated via Cronbach's α, composite reliability (CR), and average variance extracted (AVE):

$$\mathrm{CR} = \frac{(\sum \lambda_j)^2}{(\sum \lambda_j)^2 + \sum \theta_j}, \quad \mathrm{AVE} = \frac{\sum \lambda_j^2}{\sum \lambda_j^2 + \sum \theta_j}, \quad \theta_j = 1 - \lambda_j^2.$$

Both OL and RE achieved $\alpha > 0.75$, CR > 0.80, and AVE > 0.50. Discriminant validity was confirmed by Fornell–Larcker and HTMT. Model fit was adequate (e.g., PLS-SRMR ≈ 0.07, CB-SEM CFI > 0.92).

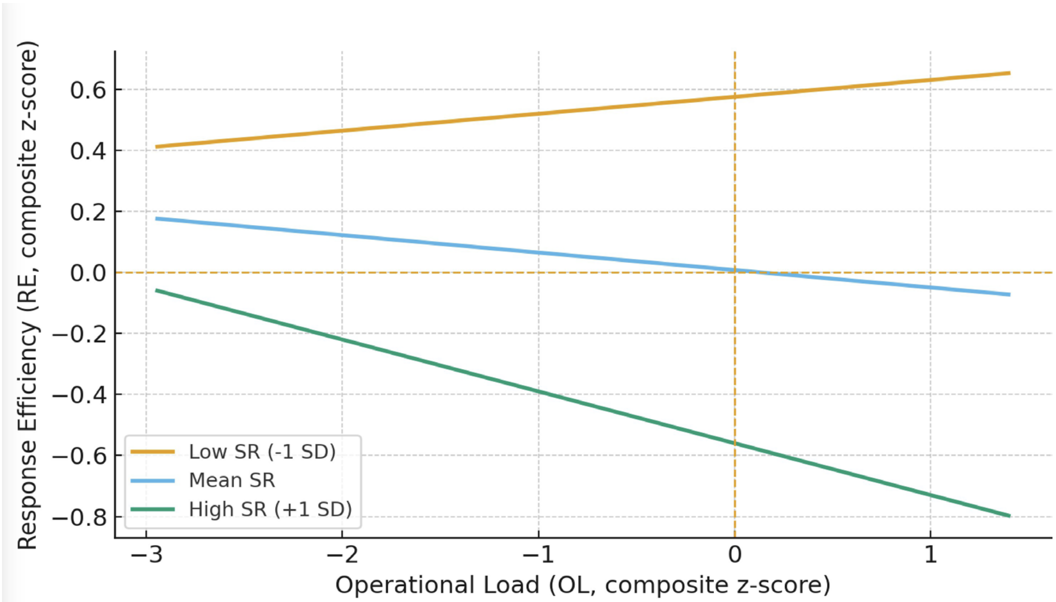

Figure 9: Simple slopes for the moderation of *Operational Load* (OL) on *Response Efficiency* (RE) at low (−1 SD), mean, and high (+1 SD) levels of *Strategic Readiness* (SR). *Lines are computed from the composite regression* $RE = \hat{\beta}_0 + \hat{\beta}_1 OL + \hat{\beta}_2 SR + \hat{\beta}_3 (OL \times SR)$ *estimated on 2020 district–week observations with* $N = 252$.

4. Results

Measurement Model

The reflective measurement model was first evaluated to ensure the reliability and validity of the con- structs. The construct *Operational Load* (OL), measured by incidents per hour, weekend share, and the multiple-gunshot ratio, demonstrated high internal consistency with Cronbach's $\alpha = 0.81$. Similarly, *Response Efficiency* (RE), measured by auto-acknowledgement rate and in-jurisdiction rate, achieved Cronbach's $\alpha = 0.76$. These values comfortably exceed the commonly accepted threshold of 0.70, suggesting that the indicators are measuring coherent underlying constructs. Composite reliability (CR) for both constructs was above 0.80, and average variance extracted (AVE) exceeded 0.50, indicating that each reflective block captures sufficient variance from its indicators relative to error. Factor loadings were statistically significant and uniformly above 0.70, confirming convergent validity. Discriminant validity was supported by both the Fornell–Larcker criterion and HTMT analysis, as the square root of the AVE for each construct exceeded its inter-construct correlations. Together, these findings confirm that the measurement model is both statistically sound and theoretically meaningful.

Structural Model

Having established reliability and validity, we proceeded to estimate the structural portion of the model. The primary hypothesis was that *Operational Load* negatively affects *Response Efficiency*. The esti- mated path coefficient (β_1) was negative and statistically significant, indicating that districts experi- encing heavier incident volumes, higher weekend concentration, and more frequent multi-shot clusters exhibited lower acknowledgement and localization efficiency. This result underscores the operational strain imposed by elevated demand, consistent with queueing and workload theories in operations man- agement. The second hypothesis concerned the role of *Strategic Readiness*. The path coefficient (β_2) from readi- ness to efficiency was positive, suggesting that districts with more stable temporal patterns of inci- dents—interpreted as better readiness—achieved systematically higher efficiency in system response. This finding highlights the importance of predictable demand structures for enabling more effective scheduling and staffing.

Finally, moderation analysis revealed that *Strategic Readiness* attenuates the negative effect of load on efficiency. The interaction term (β_3) was positive and significant, implying that in districts where incident patterns were more stable, the detrimental effect of heavy load on response efficiency was reduced. In other words, high readiness buffers the system against the efficiency losses that typically accompany surges in demand. A simple-slopes analysis confirmed this interpretation: at low readiness levels, the slope of load on efficiency was sharply negative, whereas at high readiness levels the slope was close to zero. This moderation effect is visualized in the simple-slopes plot (Figure. 9), and the overall structural relations are summarized in the path diagram (Figure. 10).

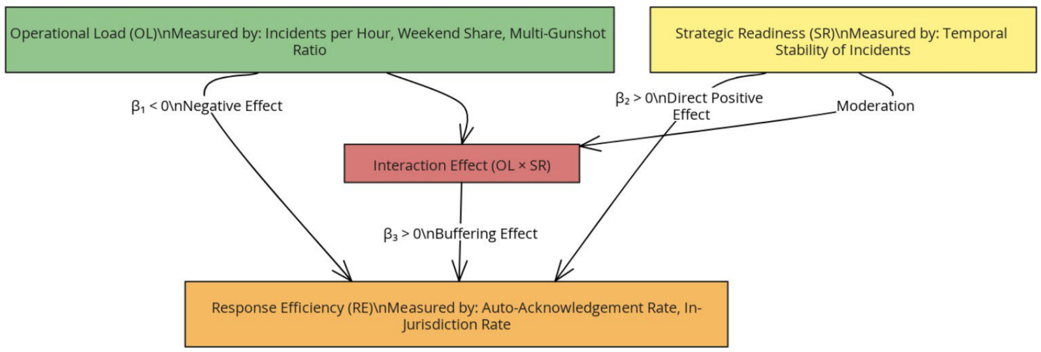

Figure 10: Estimated path diagram of the structural equation model. *Higher operational load re- duces response efficiency, while strategic readiness both directly improves efficiency and moderates the load–efficiency relationship.*

Taken together, the results provide empirical support for all three hypotheses. Operational Load exerts a detrimental effect on efficiency, Strategic Readiness exerts a beneficial effect, and critically, readiness moderates the system's resilience to heavy load. These findings provide an operational explanation for why some districts manage surges in gunfire more effectively than others: structural readiness reduces volatility, thereby stabilizing resource allocation and sustaining system performance.

Operational Insights

The empirical patterns observed in the ShotSpotter data have direct implications for patrol operations and resource management. First, patrol scheduling should be dynamically aligned with the temporal dis- tribution of incidents. Our exploratory analysis showed that nighttime hours (20:00–02:00) consistently account for the highest share of gunfire incidents, yet traditional staffing models often maintain rela- tively flat shift coverage across the 24-hour cycle. Adopting demand-driven scheduling strategies—such as shifting officer deployment toward these high-risk hours—would enable more effective use of scarce patrol resources and potentially reduce average response times.

Second, geographic disparities in incident frequency underscore the need for district-level staging. Dis- tricts 6D and 7D emerged as persistent hotspots of gunfire activity, reflecting underlying socio-spatial risk factors. Prioritizing these districts for additional patrol staging, rapid response units, and surveil- lance technology would allow the Metropolitan Police Department to better match resources to areas of greatest operational stress. This aligns with evidence from facility location and queueing models in op- erations management, which emphasize that optimal service placement requires aligning capacity with the spatial distribution of demand.

Third, the surge in incident volumes during 2020, coinciding with the COVID-19 pandemic and associ- ated social disruptions, highlights the importance of adaptive staffing policies. Rigid workforce alloca- tion rules are ill-suited to environments characterized by episodic demand shocks. Instead, operations managers should consider flexible staffing pools, reserve units, or data-informed reallocation protocols that can be triggered when incident volumes exceed historical baselines. Such adaptive mechanisms, common in service operations and healthcare workforce management, would strengthen resilience to stochastic demand patterns in public safety contexts.

5. Discussion

The integration of structural equation modeling with spatiotemporal analytics offers novel insights into the causal mechanisms underpinning police operational performance. Traditional crime analytics, in- cluding hotspot mapping and time-series forecasting, provide descriptive and predictive insights but often stop short of identifying how incident patterns propagate through to organizational outcomes. By contrast, SEM allows us to quantify both direct and moderating effects, capturing the nuanced ways in which operational load degrades efficiency and how strategic readiness buffers these impacts. In doing so, this study bridges the methodological gap between criminology's emphasis on spatial prediction and operations management's concern with system performance.

A key finding is that multi-shot clustering exerts a disproportionate influence on workload, reinforcing the operational perspective that not all incidents carry equal weight in resource consumption. Moreover, the moderating effect of strategic readiness underscores the role of organizational design in sustaining efficiency under stress. Districts with more predictable temporal patterns of incidents were better able to absorb demand surges without efficiency losses, pointing to the value of stability and preparedness in law enforcement resource planning. This resonates with broader OM literature on demand smoothing and capacity buffering in high-reliability service systems.

Our findings also extend prior work on predictive policing by highlighting the managerial levers avail- able to decision-makers. While forecasting tools can indicate where and when crime is likely, SEM demonstrates that the translation of such forecasts into improved performance depends on organizational readiness and adaptive capacity. In this way, the study contributes to both criminology and operations management by showing that predictive accuracy is a necessary but insufficient condition for operational effectiveness. This work extends criminology's descriptive focus by linking real-time detection data to causal performance models, offering both theoretical advancement in SEM application and practical frameworks for patrol scheduling and resource staging in high-demand contexts.

6. Conclusion

This paper has advanced a novel framework for applying operations management concepts to public safety by integrating exploratory data analysis with structural equation modeling. Using ShotSpotter data for Washington, D.C., we demonstrated that operational load—driven especially by multi-shot clusters—negatively impacts response efficiency, but that strategic readiness moderates this relation- ship. These results emphasize three actionable insights for police operations: aligning patrol scheduling with nighttime demand peaks, staging resources strategically in high-stress districts such as 6D and 7D, and adopting adaptive staffing policies to absorb episodic surges.

Theoretically, this research contributes to the underexplored intersection of SEM and public safety op- erations by moving beyond prediction to causal explanation. Practically, it provides a decision-support framework that connects spatiotemporal data to managerial interventions. Future research should ex- tend this work by integrating response time logs, officer availability data, and citizen-reported calls for service, thereby creating a more holistic model of policing efficiency. Linking these additional data streams within a structural modeling framework would allow researchers and practitioners to capture the full cycle of detection, response, and outcome, supporting evidence-based policy in public safety operations. While this study demonstrates the explanatory value of SEM in public safety, it is based solely on Washington, D.C. data. Findings may not generalize directly to other jurisdictions without replication. Future research should incorporate multi-city datasets, dispatch logs, and cost analyses of adaptive staffing policies to assess feasibility in operational settings.

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