Socioeconomic Drivers of Adult Disproportionate Minority Contact

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***Abstract*—Disproportionate Minority Contact (DMC) refers to the overrepresentation of certain populations within the criminal justice system relative to their share of the general population [3]. Historically, research in this field defines 'minority' mainly through the lens of race and ethnicity among juvenile populations [2]. This is reflected in a 2025 Texas study where Black youth account for 29.3% of referrals to juvenile probation despite making up only 11.3% of the state's juvenile population [10]. However, discussions with local law enforcement and jail administrators confirm the age of most inmates to be in their twenties or thirties [5]. Additionally, they suggest that factors beyond race, including gender, poverty, housing instability, and limited access to support services [6] may contribute to higher rates of arrest and jail intake for certain demographic groups, raising concerns about equity, fairness, and institutional trust.**

This research broadens the definition of DMC to encompass adult populations, examining how diverse socioeconomic factors account for disproportionate contact within the Jefferson Area Criminal Justice System (JACJ) focusing on Charlottesville and Albemarle County in particular. This study also advances the findings of the 2020 Adult DMC Final Report [6] expanding its findings to include localized qualitative data and to account for Albemarle-Charlottesville jurisdictional characteristics. Unlike the 2020 report's limited conclusions, this research provides context-specific strategies tailored to the unique infrastructure of the Jefferson Area Criminal Justice System.

The methodology merges Albemarle-Charlottesville Regional Jail (ACRJ) booking records with U.S. Census tract data through a pipeline using approximate string matching and geocoding. Census tracts are segmented via K-Means clustering, while Principal Component Analysis (PCA) identifies key structural drivers. The resulting classification system maps the intersection of systemic disadvantage and criminal justice involvement across the diverse landscape of the Albemarle-Charlottesville region.

Results show that crime and system contact are concentrated in socioeconomically disadvantaged neighborhoods. K-means clustering identified four tract profiles, with higher booking rates in high-poverty areas and lower rates in affluent areas, a pattern validated by MANOVA. Black individuals are overrepresented across most tracts and concentrated in disadvantaged clusters, while White individuals are overrepresented in affluent areas. PCA indicates that socioeconomic factors explain most variation in booking rates, with demographic factors playing a limited role. The relationship between race and system contact is context-dependent and strongly positive in high-poverty areas, but weak or negative in affluent ones, demonstrating that racial disparities are largely mediated by neighborhood socioeconomic conditions.

***Keywords*—DMC, socioeconomic, clustering, PCA.**

I. Introduction

In the United States, approximately 19%, or 49.2 million people, of age 16 or older experienced contact with police in 2022 [9] and during police-initiated encounters or traffic accidents, 6% of Black individuals experienced the threat or use of force at a notably higher rate than the 2% that were White, 2% Hispanic, and 1% of other racial groups [9], showing that these interactions and their subsequent outcomes are not distributed equally across all racial groups. This was further supported by a 2019 study done by the National Bureau of Economic Research which revealed that Black and Hispanic individuals are more likely to be subjected to non-lethal force [5], such as being handcuffed or pushed to the ground, even when accounting for contextual factors including weapon carrying or finding contraband.

This practice is known as Disproportionate Minority Contact (DMC) which has traditionally been defined as "youth of color are overrepresented in the justice system" relative to their share of the general population [3]. The research presented here maintains that "disproportionate" signifies the overrepresentation of certain populations within the criminal justice system relative to their share of the general population, but expands "minority" status beyond the conventional focus on race, ethnicity, or youth populations [10]. It includes adult populations and socioeconomic factors such as poverty level, education, and regional household income. Emphasizing socioeconomic drivers is critical, as data from the Police-Public Contact Survey (PPCS) reveals that variables like employment status and categorical income levels, ranging from level 1 (below $20,000$) to level 3 (greater than $50,000$) [5], are significant descriptors of those interacting with police. Lastly, for the purposes of this research, "contact" is defined as an individual's arrest and subsequent booking into the regional jail in Charlottesville and Albemarle County, as these serve as concrete, measurable touchpoints within the legal system.

Local insights into the Jefferson Area Criminal Justice System (JACJ) confirm this socioeconomic divide. The Albemarle-Charlottesville Regional Jail (ACRJ) estimates that 98% of inmates come from low socioeconomic backgrounds [6]. The jail population, whichever averages a daily census of 296 inmates over the past 12 months, consists primarily of adults in their twenties and thirties [6]. Field observations during ride-alongs show that Charlottesville Police Department (CPD) officers "wear many hats," mediating mental health crises and domestic disputes in hotspots like "The Haven," which is a local homelessness shelter [1,8]. These community-facing efforts are often strained by staffing shortages and a growing homeless population.

The objective of this study is to broaden the understanding of DMC by examining how adult offenders in the Charlottesville-Albemarle region are impacted by diverse socioeconomic stressors. This research expands upon the 2020 Adult DMC Final Report by integrating localized qualitative data and mapping the interactions between geographic, economic, and educational variables. Specifically, this study aims to answer:

- *Research Question 1 (RQ1)*: In which neighborhoods or communities in Charlottesville does the most crime occur, and how does that relate to the socioeconomic status of people in those communities?
- *Research Question 2 (RQ2)*: To what extent does socioeconomic status mediate the relationship between race and involvement in criminal justice?

By focusing on controllable systemic drivers, the study seeks to develop evidence-based interventions that foster equity, fairness, and institutional trust within the Jefferson Area Criminal Justice System.

II. Methods

A. Research Hypothesis

This study investigates the hypothesis that Disproportionate Minority Contact (DMC) may be driven by systematic socioeconomic factors that result in a higher need for law enforcement services within specific communities, rather than being solely a product of racial bias. To test this, we define a "meaningful contact" as any legal interaction resulting in a criminal arrest and subsequent jail booking. A booking occurs whenever an individual is arrested and charged with one or more offenses. A specific individual may have multiple bookings if the individual has been arrested multiple times over a given time period. The specific criminal charge recorded by the ACRJ serves as concrete, measurable touchpoints suitable for analysis.

B. Data Acquisition and Scope

To analyze the intersection of socioeconomic stressors and criminal justice involvement, data were synthesized from two primary sources covering the Charlottesville-Albemarle region:

- *The Albemarle-Charlottesville Regional Jail (ACRJ)*: It consists of 59,826 booking records from the Albemarle-Charlottesville Regional Jail (ACRJ), spanning January 2, 2017 to January 30, 2026. Key variables in this dataset include booking number, race, charge type (felony or misdemeanor), and residential address.
- *U.S. Census Bureau*: It comprises U.S. Census Bureau data for 40 census tracts in Charlottesville and Albemarle County, capturing socioeconomic indicators such as median household income, poverty rates, and education levels from January 1, 2020 to December 31, 2024.

Together, these data sources provide a comprehensive foundation for examining the relationship between socioeconomic conditions and criminal justice involvement at both the individual and community levels. By linking detailed booking records from the ACRJ with tract-level socioeconomic indicators from the U.S. Census Bureau, the study is able to move beyond isolated observations and instead evaluate broader spatial and structural patterns. This integrated dataset enables a more nuanced assessment of whether disparities in legal system contact can be explained by underlying economic and social conditions, thereby offering a robust empirical basis for testing the research hypothesis.

C. Data Security Procedures

Consistent with the approved University of Virginia Institutional Review Board (IRB) protocol, all researchers completed CITI Program training, specializing in the ethical treatment of vulnerable populations and the handling of sensitive prisoner data. To ensure data integrity and confidentiality, as well as protect Personally Identifiable Information (PII), all processing was conducted within the IVY Secure Computing Environment. Access was restricted via the University of Virginia (UVA) High-Security VPN, which provided a secure remote desktop interface. This infrastructure ensured that all address-matching and data-merging processes were conducted in a siloed, encrypted environment, with de-identification occurring prior to final analysis.

D. Data Cleaning and Processing

The core challenge of this methodology involved merging disparate datasets that lack a common unique identifier. Therefore, prior to any processing, an extensive data cleaning and de-duplication phase was conducted to address common issues in administrative records and ensure analytical consistency. This process included standardizing variable formats, correcting entry errors, removing incomplete or invalid records, and resolving duplicate entries to ensure that each observation represented a unique instance of system contact. De-duplication relied on combinations of booking identifiers, names, dates, and address fields, helping to reduce noise and prevent bias in downstream analyses. In addition to these foundational steps, several key transformations were applied to prepare the dataset for comparison and modeling:

- *Variable Standardization*: Socioeconomic fields, including median household income and poverty percentages, were converted to numeric types, with missing or non-applicable values coded 'N/A' for categorization.

- *Metric Creation*: A "Booking Rate" metric was calculated, defined as the number of bookings per 1,000 residents, allowing for meaningful comparisons across census tracts with varying population sizes.
- *Feature Scaling*: Key socioeconomic variables were standardized using z-score normalization to place them on a common scale and prevent large-range variables (e.g., income) from dominating results. Because z-scores do not remove the influence of extreme values, median-based metrics were used for cluster comparisons to reduce sensitivity to outliers. However, the averages of medians were taken at some points in the process.

Together, these preprocessing steps established a clean, de-duplicated, and analytically consistent dataset, providing a reliable foundation for the joining process which can be seen in Figure 1: A data pipeline was developed to integrate jail booking records with census data into a unified analytical framework. Residential addresses were first geocoded (Figure 1, Step 1) into geographic coordinates using a GIS engine [4], with approximate string matching (ASM) applied to correct inconsistencies such as misspellings and formatting variations in address data. Following standardization, each record was assigned to a census tract, enabling linkage between individual-level criminal justice data and tract-level socioeconomic indicators. This process produced a spatially enriched dataset suitable for analysis of neighborhood-level patterns. The final dataset reflects substantial data refinement, with 59,826 charges reduced to 3,232 successfully matched records. These matched records comprise 685 unique bookings across 40 census tracts, 28 in the county and 12 in the city, and form the basis for all subsequent analyses.

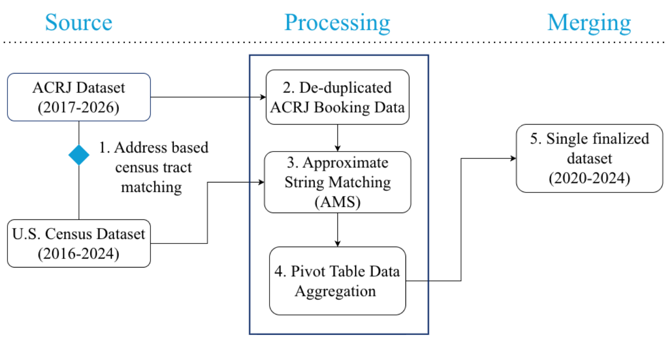

Fig. 1. The two datasets combined in analysis and how they were processed for intended results.

E. Analytical Framework

This research uses K-means clustering to group census tracts into distinct socioeconomic cohorts based on indicators such as income, poverty, education, and homeownership, enabling "like-with-like" comparisons across communities. Disproportionality analysis then assessed the overrepresentation of Black individuals in booking records within these clusters, while Principal Component Analysis (PCA) and Multivariate Analysis of Variance (MANOVA) were used to evaluate the relative influence and interaction of socioeconomic conditions and racial composition on booking rates. Statistical significance was assessed using p-values to provide a continuous measure of evidence, and rolling averages (2020–2024) were applied to stabilize socioeconomic indicators, ensuring a more reliable and nuanced analysis of how structural conditions shape criminal justice involvement.

III. Results

A. Socioeconomic Cluster Identification

To address RQ1 regarding the concentration of crime across Charlottesville and Albemarle County and its relationship to neighborhood socioeconomic status, the 40 census tracts were grouped using a K-Means clustering algorithm (k = 4). This method produced 4 distinct socioeconomic profiles reflecting meaningful gradients in wealth, education, and poverty. Furthermore, the assumption of independence of observations was satisfied as each tract represents a non-overlapping geographic unit. These preprocessing steps ensure that the resulting cohorts meaningfully reflect the underlying socioeconomic structure of the region rather than artifacts of scale or data anomalies. The cluster profiles described in Table 1 and visualized in Figure 2 provide the structural foundation for comparing patterns of criminal justice involvement across neighborhoods. As shown, Cluster 0 represents the most affluent cohort, characterized by the highest median income and homeownership alongside the lowest booking rate (3.57). Conversely, Cluster 1 represents the most disadvantaged cohort, displaying the highest poverty rate (28.8%) and the highest booking rate (5.97). Interestingly, Cluster 3 exhibited the lowest overall booking rate (3.08) despite having the lowest homeownership rate (18.3%), suggesting that the interplay between residential stability and system contact is influenced

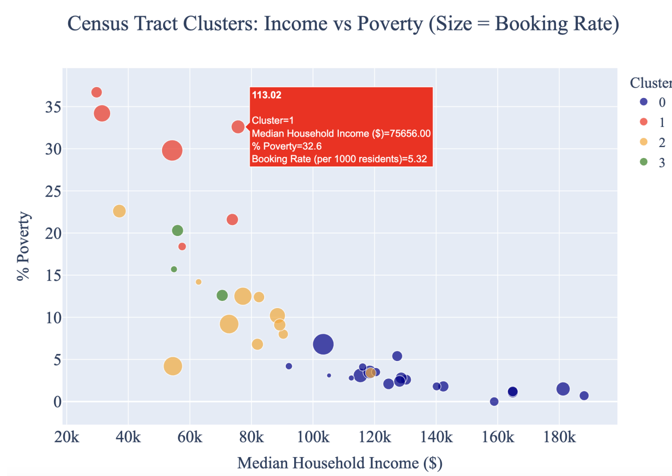

Fig. 2. This bubble plot illustrates the relationship between median household income and poverty levels across four census tract clusters, where the bubble size indicates the booking rate per 1,000 residents. The graph is interactive and shows additional information about the census tract.

TABLE I
SOCIOECONOMIC CLUSTER PROFILES AND BOOKING RATES

Cluster	Category	Income	% Pov	% BA+	% Own	% Black	% White	Rate	N
0	Affluent / Highly Educated	$133,150	2.73%	58.95%	84.34%	8.03%	81.21%	3.57	20
1	Disadvantaged / High Poverty	$53,728	28.88%	36.02%	29.42%	19.67%	54.75%	5.97	6
2	Upper-Middle / Educated	$77,776	10.24%	51.45%	52.48%	12.80%	72.32%	5.55	11
3	Working-Class / Moderate Poverty	$60,446	16.20%	40.67%	18.33%	18.93%	61.60%	3.08	3

by complex, non-linear factors. These clusters provide the necessary structural foundation for comparing patterns of criminal justice involvement across disparate neighborhood types.

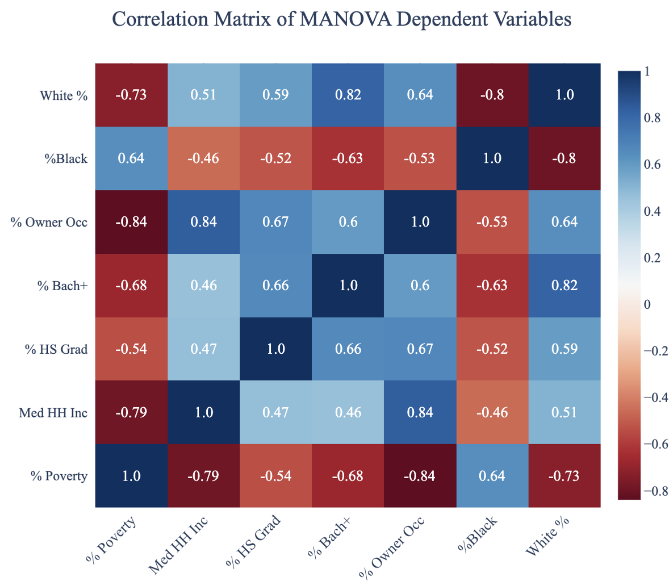

Fig. 3. Correlation matrix of MANOVA dependent variables to show multicollinearity is present, but non-influential in regards to differentiating cluster groups as a whole.

To validate the neighborhood profiles, MANOVA was conducted across seven socioeconomic and demographic characteristics. While independence was met, other assumptions required scrutiny:

- *Normality:* Shapiro-Wilk tests showed non-normal distributions for "% HS Grad" (Cluster 2) and "% Owner Occ" (Cluster 0). However, MANOVA is generally robust to moderate violations, especially given our sample of 40 (20, 6, 11, 3). Because violations were not widespread, minor deviations are tolerable for a highly significant result.
- *Homoscedasticity:* Levene's test indicated unequal variances for "% Poverty," "% HS Grad," "% Owner Occ," and "% Black." While this is a critical assumption, Pillai's Trace is robust to violations of variance-covariance homogeneity, particularly with unequal sample sizes. Its highly significant result ($p < 0.0001$) confirms overall differences between clusters.
- *Multicollinearity:* The correlation matrix seen in Figure 3 revealed several high correlations (e.g., % Poverty with Median Household Income at -0.79; % Bachelor's+ with % White at 0.82; % Black with % White at -0.80; % Poverty with % Owner Occupied at -0.84). While correlations above 0.8 complicate interpretation of individual variables, they do not invalidate MANOVA's ability to test overall group differences.

The highly significant MANOVA results (all $p < 0.0001$) confirm that the K-Means clustering successfully partitioned the census tracts into four statistically distinct groups based on their combined socioeconomic and racial characteristics.

B. Racial Representation and Structural Disparity

To assess the extent of socioeconomic status mediating the relationship between race and criminal justice involvement (RQ2), an analysis of booking records reveals a consistent pattern of structural disparity visible in Figure 4:

Fig. 4. Compares booking rates per 1,000 residents against the percentage of Black and White populations across four census tract clusters, showing higher socioeconomic conditions are associated with lower crime rates across all racial compositions.

Black individuals are overrepresented in 85–90% of regional census tracts, whereas White individuals are proportionately represented or underrepresented in 70–75% of tracts. While these disparities in exposure persist across all neighborhood types, Table 2 demonstrates that racial populations are not uniformly distributed but are heavily concentrated within specific socioeconomic environments. Affluent tracts (Cluster 0) are characterized by a significant underrepresentation of Black residents (-32.58% relative to baseline) and an overrepresentation of White residents (+10.75%). Conversely, disadvantaged, high-poverty tracts (Cluster 1) exhibit a stark overrepresentation of Black residents (+65.23%) and a corresponding underrepresentation of White residents (-25.33%), with similar overrepresentation observed in working-class tracts (+59.07% in Cluster 3). This geographic concentration suggests that

TABLE II
RACIAL REPRESENTATION ACROSS SOCIOECONOMIC CLUSTERS

Cluster	**Category**	**% Black**	**% White**	**Black Δ**	**White Δ**	**Black Rep.**	**White Rep.**
0	Affluent / Highly Educated	8.03%	81.21%	-32.58%	+10.75%	Underrep.	Overrep.
1	Disadvantaged / High Poverty	19.67%	54.75%	+65.23%	-25.33%	Overrep.	Underrep.
2	Upper-Middle / Educated	12.80%	72.32%	+7.54%	-1.37%	Overrep.	Proportional
3	Working-Class / Moderate Poverty	18.93%	61.60%	+59.07%	-15.99%	Overrep.	Underrep.

the "contact" experienced by different racial groups is fundamentally shaped by the socioeconomic characteristics of their neighborhoods.

By linking tract-level demographic baselines with individual booking rates, the study moves beyond simple aggregate counts to evaluate how neighborhood context mediates system involvement. The data indicates that Black residents are disproportionately funneled into neighborhood clusters associated with higher overall booking rates, while White residents are overrepresented in affluent areas where system contact is minimized. This structural alignment supports the hypothesis that racial disparities in the Charlottesville-Albemarle region are significantly confounded by local economic environments, necessitating a nuanced approach to criminal justice reform that addresses the intersection of race and neighborhood-level socioeconomic stressors.

C. Socioeconomic Drivers vs Demographic Factors

A combination of dimensionality reduction and correlation analysis was employed to answer RQ2 as well. Principal Component Analysis (PCA) reduced the 13 variables to two primary components accounting for 73% of the total variance. Principal Component 1 (PC1), explaining 59.2% of the variance, functioned as a "Socioeconomic Spectrum," where negative scores correlated with higher poverty and minority representation, while positive scores aligned with higher income and predominantly White populations. Visualization of these scores (Figure 5) demonstrated that tracts with lower booking rates clustered on the affluent end of PC1, whereas higher booking rates were concentrated in disadvantaged tracts. PC2, representing demographic factors like age and gender, accounted for 13.8% of the variance but showed no strong relationship with booking rates, reinforcing that socioeconomic conditions are the dominant structural driver of system contact. Principal Component 1 (PC1), which explains about 59% of the total variance, represents the dominant socioeconomic and demographic gradient across census tracts: variables such as Median Household Income, % HS Grad, % Bach+, % Owner Occupied, White %, Median Age, and % Enrolled load positively (right side), indicating more affluent, educated, older, and predominantly white areas, while % Poverty, % Black, % Hispanic, and % Asian load negatively (left side), reflecting less affluent and more racially/ethnically diverse areas; Principal Component 2 (PC2), accounting for roughly 14% of the variance, captures secondary, orthogonal patterns, where positive loadings (upper side) include % Poverty, % Asian, and education-related variables (% HS Grad,

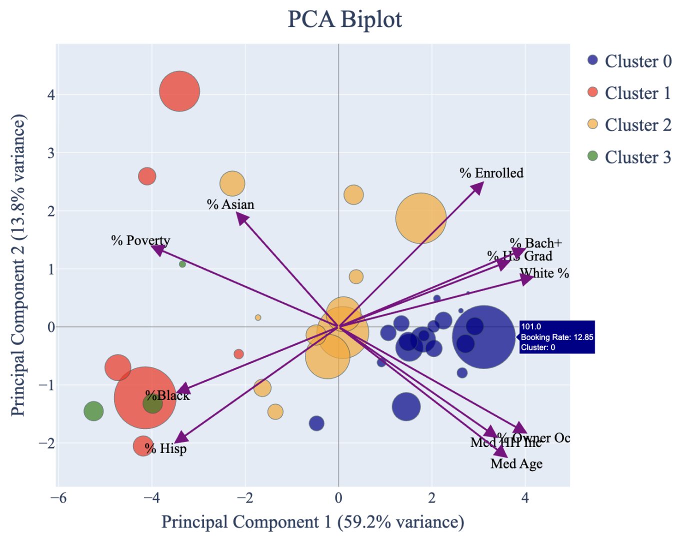

Fig. 5. Biplot shows relationship between census tracts, underlying socioeconomic and demographic characteristics (represented by PC feature arrows), and corresponding booking rates. Each point represents a census tract, colored according to its assigned cluster and scaled in size based on its 'Booking Rate'. The arrows indicate the direction and strength of influence of the original features on the two principal components. It has a hovering feature that shows the tract number, booking rate, and cluster of each dot.

% Bach+, % Enrolled), suggesting areas with a mix of higher poverty, Asian population presence, and some educational engagement, whereas negative loadings (lower side) include Median Household Income, % Owner Occupied, % Black, % Hispanic, and Median Age, indicating relatively older, lower-income, and less educated populations with higher Black and Hispanic representation; when examining cluster distribution and booking rates (with point size indicating booking rate), Cluster 0 (dark blue) lies mostly on the positive side of PC1, consistent with affluent, predominantly white characteristics and generally smaller point sizes (lower booking rates), Cluster 1 (red) and Cluster 2 (orange) are concentrated on the negative side of PC1, reflecting higher poverty and diversity and showing larger point sizes (higher booking rates), while Cluster 3 (green), although also on the negative side and characterized by low income and very low homeownership, tends to have smaller points, indicating comparatively lower booking rates; overall, the biplot highlights that the primary separation among tracts is driven by affluence and racial composition, with higher booking rates concentrated in less affluent, more diverse areas (though not uniformly, as seen with Cluster 3), demonstrating that booking rates are shaped by a multidimensional combination of socioeconomic and demographic factors rather than any single variable.

IV. Conclusion and Implications

The primary finding of this analysis is that socioeconomic conditions, most notably poverty, serve as dominant structural drivers of variation in booking rates across the Charlottesville-Albemarle region, operating both independently and in interaction with race. Although racial disparities in criminal justice contact are consistently observed in the majority census tracts, their magnitude is neither uniform nor random. Instead, these disparities are spatially concentrated within neighborhoods characterized by elevated poverty, lower homeownership, and reduced access to economic opportunities.

Additionally, the results demonstrate that the interaction between percent Black population and poverty is the most statistically significant predictor of booking rates. This finding challenges interpretations that treat race as an isolated or uniformly predictive factor in criminal justice involvement. Rather, the effect of race is highly context-dependent: in high-poverty environments, increases in the Black population are strongly associated with higher booking rates, whereas in more affluent tracts, this relationship attenuates or, in some cases, reverses. This conditional relationship indicates that racial disparities are amplified within structurally disadvantaged settings, suggesting that observed disproportionality is deeply intertwined with place-based socioeconomic inequality rather than attributable to racial composition alone.

Supporting analyses, including Principal Component Analysis and cluster-level comparisons, further reinforce that structural disadvantage, as captured through multidimensional indicators of poverty, education, and housing stability, accounts for the majority of variation in booking rates. Demographic factors independent of these conditions exhibit comparatively limited explanatory power. In this sense, the findings provide strong empirical support for the study's central hypothesis: that Disproportionate Minority Contact (DMC) is significantly mediated by systemic socioeconomic factors that shape both exposure to and interaction with the criminal justice system.

Taken together, these results directly address both research questions. In response to RQ1, higher concentrations of criminal justice contact are found in economically disadvantaged neighborhoods, not simply those with particular racial compositions. In response to RQ2, socioeconomic status emerges as a critical mediating force that conditions the relationship between race and system involvement, transforming what may appear as racial disparity into a more complex, structurally embedded phenomenon.

These findings carry important implications for policy and intervention. Efforts aimed solely at addressing racial disproportionality without confronting underlying socioeconomic inequities are unlikely to produce sustained reductions in system involvement. Instead, strategies that target poverty alleviation, housing stability, educational access, and community-level investment may be more effective in reducing both overall booking rates and the racial disparities observed within them. By shifting the focus from individual-level characteristics to structural conditions, this study underscores the importance of place-based, equity-driven approaches to criminal justice reform.

Future research will extend this analysis by incorporating emergency dispatch (911) data to distinguish between citizen-initiated and officer-initiated encounters. This distinction is essential for disentangling non-discretionary system contact from discretionary enforcement practices. Such an approach will enable a more precise evaluation of whether elevated booking rates reflect underlying differences in crime incidence, variations in reporting behavior, or differential patterns of policing across socioeconomic contexts. Ultimately, this line of inquiry will further clarify the mechanisms through which structural disadvantage translates into criminal justice involvement.

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