Journal of Criminal Justice 99 (2025) 102473

Contents lists available at ScienceDirect

Journal of Criminal Justice

journal homepage: www.elsevier.com/locate/jcrimjus

Spatiotemporal population mix (SPM) as a criminogenic mechanism: Testing environmental-criminology hypotheses with mobility clusters derived from mobile-device geotracking

Olga B. Semukhina [a,*], Junghwan Bae [a], Stan Korotchenko [a], Christopher Copeland [a,b]

[a] Tarleton State University, Department of Criminal Justice, 10850 Texan Rider Drive, Fort Worth, TX 76036, United States of America
[b] Tarleton State University, Department of Computer Science and Electrical Engineering, 10850 Texan Rider Drive, Fort Worth, TX 76036, United States of America

ARTICLE INFO

Keywords:
Spatiotemporal population mix
Human mobility
Ambient population
Residential stability
Population heterogeneity
Victimization
Spatial concentration
Violent crime
Property crime
Drug crime

ABSTRACT

Crime pattern theory and contemporary environmental criminology posit that crime risk is shaped not only by where people are but by how they circulate, converge, and anchor in urban space. This study advances that theoretical tradition by introducing the Spatiotemporal Population Mix (SPM)—a multidimensional construct that captures visitor-origin diversity, travel distance, stop frequency, dwell duration, and nighttime-resident share. Using year-long GPS traces from 166 census block groups in Arlington, Texas, three SPM profiles were identified via k-means clustering (Stable-Residential, Moderate-Mobility, and High-Transience) and evaluated with generalized spatial two-stage least-squares models. Block groups exhibiting a High-Transience SPM recorded violent, property, and drug-crime rates two-to-three times higher than Stable-Residential areas, net of social disorganization, land use, and spatial spillovers. Complementary continuous analyses confirmed that transient SPM facets—long travel, frequent stops, and diverse origins—elevate crime risk, while residential anchoring—long dwell and high nighttime-resident share—suppresses it. By demonstrating that the SPM explains crime above and beyond static population counts, the study refines routine activity and crime-pattern theory, offers a replicable behavioral metric for place-based research, and points practitioners to a small set of transient micro-areas that disproportionately drive urban crime.

Crime pattern theory, alongside recent empirical extensions of routine activity theory, suggests that crime risk is shaped by how people move through urban spaces, as well as how far and how often they travel (Brantingham & Brantingham, 1993; Malleson & Andresen, 2015). Institutionalizing this perspective, research shows that crime often emerges when routine movements bring offenders and suitable targets together in micro-locations at times lacking capable guardianship (Brantingham & Brantingham, 1995; Cohen & Felson, 1979). In addition, more recent environmental-criminology studies have demonstrated that specific land-use mixes channel predictable flows of individuals (Eck, Clarke, & Guerette, 2007; Weisburd, Groff, & Yang, 2012), that offender motivation fluctuates alongside these mobility patterns (Bernasco & Block, 2011; Wortley & Townsley, 2016), and that place managers can disrupt or amplify crime opportunities by shaping or monitoring these flows (Felson & Eckert, 2018; Mazerolle, Wickes, & McBroom, 2010).

Previous criminological research has typically relied on static, census-based population measures, which do not account for the dynamic characteristics critical to understanding spatiotemporal crime risk—namely, the distinction between residents and visitors and their respective movement patterns (Andresen & Jenion, 2010; Malleson & Andresen, 2015). In contrast, human mobility data derived from geotracked cellphone devices—a methodology that has gained widespread adoption in geographic information science (GIS) and criminology over the past decade—provides granular insights into when and how individuals traverse urban space (Barbosa et al., 2018; Jiang, Ferreira, & González, 2012). These data enable researchers to measure mobility along key dimensions such as travel distance, stop frequency, dwell duration, and the diversity of origin locations. Such metrics align with theoretical mechanisms central to contemporary environmental criminology, including convergence (where inflow from multiple origins increases the co-presence of offenders and targets), guardianship dilution (where high turnover and short stays reduce natural surveillance), and target suitability (where long-distance visitors may be less familiar with

* Corresponding author.
E-mail address: semukhina@tarleton.edu (O.B. Semukhina).

https://doi.org/10.1016/j.jcrimjus.2025.102473
Received 28 February 2025; Received in revised form 8 July 2025; Accepted 9 July 2025
Available online 16 July 2025
0047-2352/

the environment and thus more vulnerable to victimization). These behavioral indicators jointly define what this study terms the Spatio-temporal Population Mix (SPM)—a multidimensional construct representing who occupies urban micro-places, when, and for how long.

Because the mobility dimensions under investigation—such as inflow volume, travel distance, dwell time, and visitor origin diversity—are theoretically interrelated, this study applies multivariate k-means clustering to identify distinct neighborhood mobility profiles that reflect holistic patterns of human movement. To ensure the robustness of the findings, the analysis also includes models that incorporate the original mobility variables as continuous predictors, allowing for a comparison between profile-based and variable-based specifications.

This study contributes to criminological theory by extending routine activity theory and crime pattern theory through the use of empirical mobility data. It operationalizes core mechanisms such as convergence, guardianship, and target suitability using direct behavioral indicators—like stop frequency, dwell time, and travel distance—rather than relying on static proxies such as location of criminogenic facilities, land use or census-based commuting patterns. In doing so, it empirically tests the assumption that daily movement patterns—not just place-based features—structure opportunities for crime. It also builds on crime pattern theory by identifying distinct spatial mobility profiles that align with criminogenic place types, such as entertainment districts, residential enclaves, and mixed-use corridors.

In addition to its theoretical contributions, the study offers practical insights for spatial crime prevention. By highlighting the criminogenic significance of mobility clustering—rather than solely demographic or land-use profiles—it provides a new framework for identifying high-risk areas that may not be visible through traditional risk indicators. These findings may inform urban design, policing strategies, and resource allocation in dynamic environments.

1. Literature review

Criminological theories have long emphasized the role of population structure and human movement in shaping the opportunity for crime. Over the past two decades, advancements in spatial analysis and geospatial technologies have enabled researchers to refine how population exposure is measured and modeled in criminology. Yet much of this work has relied on static indicators of residential population, limiting the field's ability to capture the temporal and behavioral dimensions of urban life. This literature review begins by tracing the evolution of population measurement in spatial crime research, including the limitations of static and ambient metrics. It then introduces environmental criminology as a theoretical framework for understanding how movement patterns—such as inflow, stop frequency, dwell duration, and residential anchoring—may structure crime opportunity. Building on this foundation, this literature review presents prior empirical findings related to the effects of people movement of offending and victimization and outlines four hypotheses that guide the present study.

1.1. Static population measures in spatial crime research

Early research in spatial criminology has relied heavily on static, census-based data to assess the structural characteristics associated with crime patterns. The widespread adoption of geographic information system (GIS) technologies in the early 2000s enabled researchers to spatially link crime incidents to demographic and land-use variables across neighborhoods, producing more refined analyses of urban crime concentrations (Chainey & Ratcliffe, 2013; Ratcliffe, 2004). U.S. Census data, particularly through the decennial census and the American Community Survey (ACS), became foundational for measuring indicators such as concentrated disadvantage, residential instability, and racial or ethnic heterogeneity (Krivo & Peterson, 2000; Peterson & Krivo, 2010; Sampson & Raudenbush, 1999). These variables were used to operationalize classic criminological theories, including social disorganization, routine activity, and broken windows perspectives.

Despite their utility, census-based population measures offer only periodic snapshots of residential population composition. They do not account for the temporal and behavioral dynamics that influence crime opportunity throughout the day. For example, while crime incidents often occur in locations with dense foot traffic or commercial activity, static data reflect only where people reside, not where they travel, work, or congregate at specific times (Andresen, 2006, 2011). Relying exclusively on residential population estimates can misrepresent the true risk environment in neighborhoods that experience high levels of nonresident inflow (Andresen & Jenion, 2010). This limitation is particularly evident in urban centers, entertainment districts, and commercial corridors, where population exposure fluctuates markedly across hours and days (Malleson & Andresen, 2016; Sutton, Elvidge, & Obremski, 2003).

The inability of static data to capture transient or visitor-driven exposure risks has motivated researchers to explore more dynamic measures of population presence, including those based on activity patterns and real-time behavioral data. This shift toward more temporally sensitive population measurement reflects a broader recognition in environmental criminology that crime is structured not just by where people live, but by how and when they move through urban space (Brantingham & Brantingham, 1993; Weisburd et al., 2012).

Building on the move from static headcounts to behavioral measures, this study introduces a new construct—Spatiotemporal Population Mix (SPM) —to organize and interpret how neighborhood-level movement patterns shape crime opportunity. SPM is the dynamic blend of residents and visitors simultaneously present in a micro-place and is theorized along three criminologically salient facets: visitor inflow heterogeneity (how many origins and how far travelers come), movement intensity (how often people stop and circulate once present), and residential anchoring (the share of individuals who remain overnight). Whereas the umbrella term human mobility refers to any measurable movement of persons and has been operationalized inconsistently in prior research, SPM isolates only those aspects that routine-activity, crime-pattern, and place-management theories identify as mechanisms of convergence, guardianship dilution, and target suitability.

Operationalizing SPM, the study leverages anonymized mobile device geotracking data to create five behavioral indicators—non-resident origin counts, median travel distance, stop frequency, median dwell time, and nighttime-resident proportion—and tests how the resulting profiles predict neighborhood crime. The following sections unpack each facet of SPM, reviewing relevant environmental-criminology literature and detailing four hypotheses linking them to violent, property, and drug-related crimes.

1.2. Environmental criminology foundations for SPM dimensions

Environmental criminology is a broad theoretical framework that encompasses a range of theories focused on how spatial, situational, and temporal factors structure opportunities for crime. Among its most widely applied components are routine activity theory (Cohen & Felson, 1979), crime pattern theory (Brantingham & Brantingham, 1995), and place management theory (Felson & Eckert, 2018). Together, these perspectives explain how the convergence of motivated offenders, suitable targets, and the absence of capable guardians is influenced by movement patterns, land use, and situational routines. Routine activity theory provides the foundational model of opportunity, while crime pattern theory and place management approaches further specify where, when, and how those opportunities are likely to emerge in urban environments. Spatiotemporal Population Mix, already defined above, is here unpacked into its criminogenic facets—visitor inflow heterogeneity, movement intensity, and residential anchoring—each mapped to a specific opportunity mechanism.

One set of concepts central to this framework involves crime generators and crime attractors, which help explain why certain locations become criminogenic. Crime generators are places that draw high volumes of noncriminal routine activity—such as shopping centers, transit hubs, or stadiums—that inadvertently increase the likelihood of offender–target convergence due to sheer volume of foot traffic (Eck et al., 2007). In contrast, crime attractors are destinations that offenders purposefully seek out due to their perceived opportunities and low risk of detection, such as entertainment zones or drug markets. These places often experience high inflow from surrounding neighborhoods and tend to attract both victims and offenders who are not embedded in local social networks, weakening guardianship and collective efficacy (Bernasco & Block, 2011).

The criminogenic potential of these spaces is further shaped by the dynamic nature of offender motivation and local guardianship. Recent research suggests that offender motivation is not static but situationally triggered by environmental cues, target availability, and local land-use patterns (Wortley & Townsley, 2016). Simultaneously, place management theory highlights the influence of on-site actors—such as business employees, security personnel, and residents—in shaping the degree of oversight and informal control within a given area (Felson & Eckert, 2018; Mazerolle et al., 2010). Taken together, these theoretical strands suggest that crime risk is shaped not only by structural disadvantage or residential composition but also by who moves through a place, how often, and for what purposes.

Informed by this perspective, the present study examines how the diversity of origin areas from which visitors travel to a neighborhood—visitor inflow heterogeneity, defined as the number of unique origin CBGs and their median travel distance (Malleson & Andresen, 2016)—may influence crime rates. A high number of origin locations suggests that a neighborhood is a node in a broader mobility network, likely attracting a more heterogeneous and unfamiliar population. Such diversity may increase the likelihood of offender–target convergence, reduce the effectiveness of local guardianship, and undermine informal social control. In addition, longer median travel distances signal that many visitors originate well outside adjacent neighborhoods, further amplifying anonymity and weakening local guardianship. Prior studies have found that areas with higher levels of nonresident inflow experience greater rates of robbery and assault, reinforcing the role of spatial convergence in driving crime opportunities (Andresen & Jenion, 2010; Bernasco & Block, 2011). Accordingly, this study hypothesizes that block groups with greater visitor inflow heterogeneity will exhibit higher rates of violent, property, and drug-related crime.

1.3. Movement intensity and target convergence

The second facet of SPM—movement intensity—captures how often mobile devices stop and circulate once inside a place. High stop frequency signals concentrated activity and repeated presence by large numbers of individuals, which may lead to more frequent spatial and temporal convergence of offenders and potential targets. From a routine activity perspective, this convergence heightens the probability of criminal opportunity, especially in locations lacking adequate guardianship (Cohen & Felson, 1979).

Environmental criminology further emphasizes that repeated, predictable flows of activity—such as those observed in shopping centers, nightlife corridors, or transit nodes—structure opportunities for crime by creating stable routines in which potential victims and motivated offenders intersect (Brantingham & Brantingham, 1995; Eck et al., 2007). Locations with high foot traffic may attract both predatory offenders and targets due to their anonymity and the abundance of accessible targets. These settings are frequently characterized as crime generators because their routine activity volumes increase the probability of encounters that can result in victimization, even when most individuals are not themselves crime-involved (Malleson & Andresen, 2016; Weisburd et al., 2012).

Stop frequency can also reflect spatial churn, particularly in environments marked by short visits and low social investment. Prior research indicates that neighborhoods with dense and repetitive pedestrian flows often experience elevated crime rates, including street-level robbery and theft, due to the routine availability of transient targets and the reduced likelihood of informal social intervention (Bernasco & Block, 2011; Felson & Eckert, 2018). Accordingly, neighborhoods with higher movement intensity are expected to exhibit elevated violent, property, and drug-related crime rates, as frequent visitation increases both exposure and opportunity for illicit transactions and interpersonal conflict.

1.4. Residential anchoring and informal control

The third facet of SPM—residential anchoring—reflects how firmly a location is occupied by people who remain overnight. This metric approximates the presence of individuals who reside in the area and are likely to have more consistent exposure to their surroundings. Routine activity theory suggests that residents—especially those who are present in the evenings and overnight—are more likely to serve as capable guardians by engaging in informal surveillance, maintaining social ties, and contributing to territorial functioning (Cohen & Felson, 1979; Felson & Eckert, 2018).

The criminological literature has long emphasized the importance of residential stability and community investment in shaping collective efficacy and neighborhood control. Sampson, Raudenbush, and Earls (1997) found that areas with higher residential stability and stronger neighborhood attachment were more capable of mobilizing informal social control. Subsequent studies demonstrated that neighborhoods with more consistent resident presence exhibited lower levels of violent and property crime, even when controlling for structural disadvantage. These effects are theorized to operate through greater familiarity among residents, stronger expectations for appropriate behavior, and a higher likelihood of intervention in public spaces.

Studies using ambient population indicators have shown that residential anchoring is significantly associated with reduced crime risk. For example, neighborhoods with higher proportions of nighttime-resident devices tend to exhibit lower crime rates, even after accounting for total foot traffic and local land-use patterns (Malleson & Andresen, 2016). These findings suggest that the composition of the population—particularly the extent to which it reflects stable, locally invested residents rather than transient visitors—plays a critical role in shaping informal guardianship. Devices that remain overnight likely correspond to individuals who have ongoing social and spatial commitments to the neighborhood, enhancing the likelihood of monitoring, intervention, and resistance to disorder. Accordingly, block groups with a higher proportion of nighttime-resident devices are expected to exhibit lower rates of violent, property, and drug-related crime due to the protective effects of residential anchoring and stable informal control.

Relatedly, shorter median dwell times contribute to guardianship dilution because individuals neither remain long enough to exercise informal surveillance nor develop familiarity with the setting. Empirical research shows that street segments or neighborhoods characterized by longer average dwell durations—or high 'time-at-home' shares—consistently show lower rates of robbery, theft, and burglary (Bae, Korotchenko, Semukhina, & Copeland, 2025; Bogomolov et al., 2015; Hipp & Kim, 2019; Malleson & Andresen, 2016).

The reviewed literature demonstrates that traditional static population measures have limited capacity to account for the dynamic and behavioral characteristics that shape neighborhood crime risk. Environmental criminology and routine activity theory suggest that crime opportunity is structured not only by land use and demographic composition, but also by how, how far, and how often people move through space. The integration of high-resolution human mobility data allows for direct measurement of behavioral patterns long theorized to influence crime but rarely captured empirically.

Drawing on this framework, the present study operationalizes the construct of Spatiotemporal Population Mix (SPM) using five behavioral indicators—visitor origin diversity, stop frequency, dwell duration, travel distance, and nighttime-resident proportion—and tests their associations with violent, property, and drug-related crime rates across census block groups. It is expected that greater inflow from diverse origin areas will increase the likelihood of offender–target convergence, thereby elevating crime rates. Higher stop frequency is similarly predicted to increase exposure to crime due to repetitive interactions in activity-rich environments. In contrast, longer dwell times are theorized to increase natural surveillance and informal control, producing reduced crime risks. Finally, neighborhoods with a higher proportion of nighttime residents are anticipated to experience lower crime rates, reflecting stronger residential anchoring and more consistent guardianship.

Because these SPM facets are expected to covary—for example, neighborhoods with greater inflow may also have shorter dwell times and higher stop frequency—the study applies multivariate k-means clustering to identify holistic mobility profiles. To assess whether these profiles provide explanatory power beyond clusters, the analysis also incorporates each SPM facet as a continuous predictor by grouping them into two composite indices—transient mobility pattern and residential mobility pattern—and assessing their explanatory value across the entire study population. The following section details the data sources, measurement strategy, and modeling procedures used to evaluate these relationships.

2. Methods

2.1. Study area

This study focuses on the city of Arlington, Texas, the third-largest city in the Dallas-Fort Worth (DFW) Metroplex, with a population of 394,266 residents and a density of 4112.7 people per square mile (U.S. Census, 2020). Arlington was chosen as the study area for its unique combination of characteristics that make it well-suited for analyzing crime patterns at the community-level. First, Arlington serves as a mid-sized, demographically diverse urban environment that reflects a mix of residential, commercial, and recreational spaces, including major attractions like the AT&T Stadium and Globe Life Field. These features generate complex land-use configurations and high-volume visitor flows, offering a compelling context for analyzing how variation in spatiotemporal population mix relates to crime.

Geographically, Arlington is situated between Dallas and Fort Worth, at the intersection of suburban and urban dynamics—making it particularly well-suited for assessing how different neighborhood mobility profiles affect crime distribution. Importantly, the availability of address-level crime incident data from the Arlington Police Department enables detailed spatial analysis for the year 2019, prior to disruptions associated with the COVID-19 pandemic. Using 2019 data avoids anomalies in crime and mobility introduced by lockdown periods and ensures a clear interpretation of pre-pandemic patterns. The census block group (CBG) was selected as the unit of analysis due to its spatial granularity and frequent use in environmental criminology research for capturing neighborhood effects with sociodemographic homogeneity (Hipp, 2007; Wo, Rogers, Berg, & Koylu, 2024). Together, these factors position Arlington as a uniquely suitable case study for understanding the interplay between environmental and demographic factors on crime.

2.2. Data sources and measures

2.2.1. Crime data and measures

Crime incident data for 2019 were collected from the Arlington Police Department. This data included information on the location and type of crime committed. The incidents were geocoded using ArcGIS and aggregated into census block groups, achieving a match rate of approximately 97.8 %. To examine differences in crime across Arlington's census block groups, indices were constructed for violent crime (consists of counts of robberies and aggravated assaults), property crime (consists of counts of burglaries and motor vehicle thefts), and drug-related crimes (encompassing all controlled substance offenses, including possession and distribution within NIBRS codes 35 A-35B) from January 1 to December 31, 2019. To normalize the crime data, crime counts were transformed by natural logarithmic function.

2.2.2. Advan mobility data

Data Source. Behavioral data used to construct the Spatiotemporal Population Mix (SPM) measures were obtained from Advan Research Corporation,[1] a company specializing in anonymized GPS-based mobility analytics. These data—accessed through a Dewey subscription and aggregated to the census block group (CBG) level—include rich temporal and spatial detail on where mobile devices stop, how far they travel, how long they stay, and how frequently they return. This allows for fine-grained analysis of neighborhood-level population dynamics relevant to environmental criminology.

Unlike early studies that relied on self-reported human mobility via social media check-ins, GPS data from cellphones provide continuous, passively collected location information with greater spatial precision and temporal density. This enables more accurate measurement of SPM facets—such as stop frequency, dwell time, and travel distance—aligned with theoretical mechanisms of convergence, guardianship dilution, and target suitability. Moreover, GPS-derived data offer broader population coverage than social media–based sources, which tend to underrepresent older adults and lower-income groups. As of 2021, 98 % of U. S. residents owned a cellphone, compared to only 82 % who used social media platforms.

In late 2022, Advan acquired the "Human Mobility Patterns" business license from SafeGraph, integrating SafeGraph's point-of-interest geometries while refining its spatial mobility estimators. However, due to its primary application in marketing analytics, Advan excludes areas with sparse commercial activity—specifically, CBGs with fewer than 1000 points of interest or tracts with fewer than 400 POIs. In Arlington, this resulted in the omission of 86 of 252 CBGs. Fig. 1 shows the geographic distribution of sampled and excluded CBGs, revealing no meaningful spatial clustering of the excluded areas.

To assess potential biases arising from the exclusion of these 86 CBGs, Table 1 compares socio-economic and demographic characteristics between the included (Sample) and excluded (Missing) CBGs. The comparison reveals that the two groups are largely comparable across several key indicators. For instance, concentrated disadvantage (Sample: M = 0.224; Missing: M = 0.213) and residential instability (Sample: M = 0.188; Missing: M = 0.173) exhibit only minor differences. Similarly, educational attainment (bachelor's degree: Sample = 33.9 %; Missing = 31.1 %) and median household income (Sample = $75,135; Missing = $73,012) are closely aligned. Both the sample and the excluded CBGs also display similar proportions of residential land use.

However, racial composition shows some noteworthy variation. The sample contains a higher proportion of White residents (Sample: M = 0.402; Missing: M = 0.317) and a lower proportion of African American residents (Sample: M = 0.225; Missing: M = 0.311). These disparities suggest that the study may somewhat underrepresent African American populations. Nonetheless, the overall alignment in socio-economic characteristics between the two groups suggests that any bias introduced by the exclusion of CBGs is minimal.

Spatiotemporal Population Mix Measures. Advan determines a device's home census block group (CBG) by identifying its most frequent nighttime location (between 6 PM and 7 AM) over the preceding six weeks. This study used Advan's device-level location data to estimate five indicators from January 1 to December 31, 2019, that together comprise SPM – the construct that captures how residents and visitors circulate, pause, and anchor in micro-geographic spaces and serves as the behavioral foundation for this study's theoretical framework and

[1] This data was made available by Advan Research (https://advanresearch.com) via the subscription to Dewey Data platform (https://www.deweydata.io)

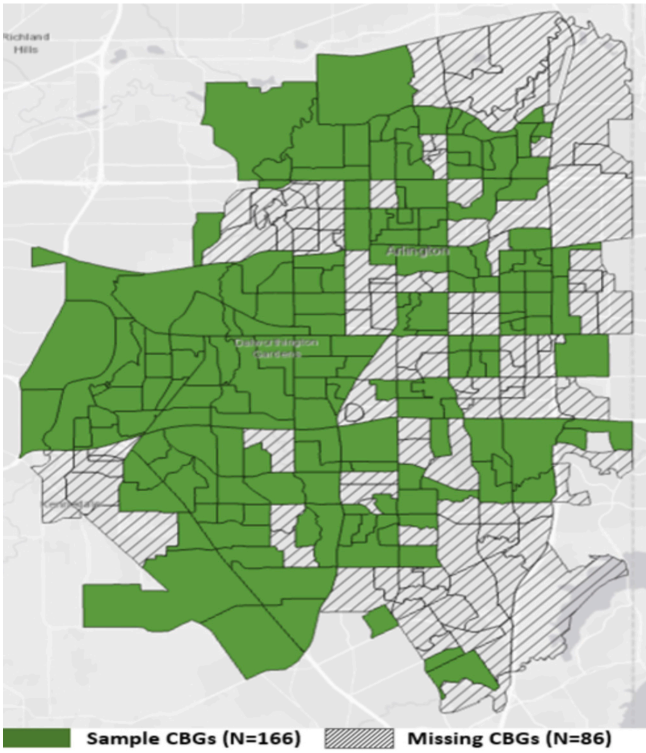

Fig. 1. Geographic Distribution of Sampled and Missing Census Block Groups (CBGs).

Table 1
Descriptive Statistics of Sample CBGs and Missing CBGs

	Sample CBGs (N = 166)		Missing CBGs (N = 86)	
	M	SD	M	SD
Concentrated disadvantage	0.224	0.111	0.213	0.156
Residential instability	0.188	0.126	0.173	0.210
Ethnic heterogeneity	0.517	0.150	0.599	0.123
Households	664.409	304.001	579.174	250.130
% old house	0.089	0.177	0.104	0.121
% aged 65	0.120	0.082	0.112	0.045
% aged 15 to 34	0.144	0.089	0.121	0.031
% Male	0.475	0.424	0.487	0.341
% Female	0.524	0.213	0.512	0.452
% bachelor's degree	0.339	0.155	0.311	0.162
White	0.402	0.159	0.317	0.114
Black	0.225	0.124	0.311	0.145
Hispanic	0.272	0.214	0.257	0.131
Asian	0.039	0.059	0.041	0.107
Population	1627.644	541.13	1346.278	456.24
Median household income	75,135	1098	73,012	1301
% Residential	0.882	0.113	0.851	0.210
% Commercial	0.035	0.140	0.024	0.119
% Vacant areas	0.014	0.020	0.089	0.024

analytic models.

The five variables—non-resident origin counts, median travel distance, stop counts per device, median dwell time, and nighttime-resident proportion—each reflect one of the three theoretical dimensions of SPM: visitor inflow heterogeneity, movement intensity, and residential anchoring. Their operational definitions are as follows.

Visitor Inflow Heterogeneity. This construct captures the diversity and spatial reach of visitors entering a given CBG. It reflects the degree to which neighborhoods attract individuals from a wide range of origins and distances, which may increase anonymity, reduce familiarity, and dilute social control. Two indicators operationalize this construct: Non-Resident Origin Counts and Median Distance from Home.

Non-Resident Origin Counts (CBG Counts of Device Travel Origins) represents the number of unique origin locations for devices that stopped in a CBG but had a designated home elsewhere. It is calculated by excluding all devices whose home CBG matches the destination CBG, then counting the distinct home CBGs of the remaining devices. Higher values suggest inflow from a broad set of origin neighborhoods or cities and may signal a neighborhood's role as a regional attractor.

Median Distance from Home measure captures the median distance, in meters, between the home CBG and the destination CBG of each device. Unlike origin counts, which reflect how many different places visitors come from, this measure captures how far they have traveled. It offers an estimate of spatial range or mobility extent and complements origin diversity by indicating whether inflows come from distant or nearby locations.

Taken together, these two indicators offer complementary views of visitor inflow heterogeneity. A block group with high origin diversity and long median travel distances is likely to be a mobility node in the regional network—such as a commercial, recreational, or service-intensive area—that draws outsiders with limited social ties to the local area. These characteristics align with criminological expectations of reduced informal control, increased convergence between motivated offenders and suitable targets, and elevated crime risk in high-transience zones. Accordingly, this study hypothesizes that census block groups with greater visitor inflow heterogeneity—as measured by both origin diversity and travel distance—will exhibit higher rates of violent, property, and drug-related crime.

Movement Intensity. The second SPM facet, movement intensity, reflects the volume and rhythm of internal circulation within a given CBG once individuals have arrived. This dimension is theoretically linked to the convergence component of routine activity theory and crime pattern theory. Areas characterized by high internal mobility are more likely to host frequent interactions among strangers, increasing the probability of convergence between potential offenders and suitable targets, especially when guardianship is limited or inconsistent.

Movement intensity is captured through two behavioral indicators: Stop Counts per Device and Median Dwell Time. These indicators jointly assess how densely and how long individuals engage with the spatial environment, offering a dynamic alternative to traditional static proxies of land use or population density.

Stop Counts per Device represents the average number of stops recorded per mobile device within a CBG. It is calculated by dividing the total number of qualifying stops by the number of unique devices observed in the area. A "stop" is defined as an instance where a device remains stationary for at least one minute, ensuring that passive pass-throughs are excluded.

Higher values indicate areas with more intensive intra-area activity—places where individuals routinely engage with multiple destinations such as stores, restaurants, or entertainment venues. These patterns are often observed in commercial corridors, nightlife districts, or multimodal transit hubs, where rapid and repeated exchanges create high exposure densities. From a criminological perspective, such environments can elevate the probability of spontaneous conflicts, opportunistic theft, or drug transactions, especially if crowding, anonymity, or lack of surveillance reduce the likelihood of intervention.

Median Dwell Time reflects the typical duration of stay, calculated as the median length of time (in minutes) that devices remained at their stop location within the CBG, considering only stops lasting at least one minute. Lower median dwell times indicate that individuals tend to exit the area quickly after brief visits—patterns typical of transactional spaces such as gas stations, take-out counters, or transportation pick-up zones. In contrast, longer dwell times suggest more sustained engagement with the space, which may reflect residential presence, prolonged commercial activity, or recreational use. In criminological terms, short dwell durations may weaken guardianship because individuals neither remain long enough to monitor their surroundings nor develop sufficient familiarity with local norms and actors. Repetitive, shallow engagements with space can create churn—constant inflow and outflow of strangers—associated with diminished informal control and increased victimization risk.

Together, Stop Counts per Device and Median Dwell Time provide a nuanced lens into the micro-rhythms of urban life. Areas with high stop counts but low dwell times are especially likely to reflect high-churn, low-stakes activity associated with convergence-fueled crime risks, whereas longer dwell durations may enhance passive surveillance and stabilize behavior. Accordingly, this study hypothesizes that block groups characterized by greater movement intensity—defined by more frequent stops and shorter dwell times—will exhibit higher rates of violent, property, and drug-related crime.

Residential Anchoring. The third and final SPM facet, residential anchoring, captures the degree to which a CBG is occupied by individuals who remain in the area overnight. This construct reflects the stability and embeddedness of a population and is theoretically linked to the guardianship and territorial functioning mechanisms emphasized in routine activity theory and place management theory. Areas with strong residential anchoring are more likely to foster social cohesion, informal surveillance, and collective efficacy—all factors that inhibit crime by increasing the likelihood of detection, intervention, or deterrence. In contrast, neighborhoods where the population turns over daily and few individuals remain overnight may lack both the observational continuity and place-based investment needed to sustain informal control.

Residential anchoring is operationalized through two indicators: Proportion of Devices Residing at Home at Night and Median Dwell Time. Together, these indicators assess not only who stays overnight but also how long people typically remain in a place—both important proxies for rootedness and situational guardianship.

Proportion of Devices Residing at Home at Night estimates the share of mobile devices in a CBG whose nighttime location is classified as "home" based on their movement history over the previous six weeks. It is calculated by dividing the number of nighttime-home devices by the total number of devices observed during the daytime in the same CBG. High values suggest that the area is predominantly residential and inhabited by individuals who are likely to have sustained social ties to the neighborhood. These residents are assumed to be more familiar with their environment, more invested in its safety, and more likely to engage in or support informal surveillance (Cohen & Felson, 1979; Sampson et al., 1997). In contrast, low proportions imply that most devices present during the day belong to non-residents, such as commuters or customers, whose presence is transient and whose incentives to monitor or intervene are minimal.

Although also interpreted as part of movement intensity, Median Dwell Time—when analyzed within residential zones—functions as a proxy for population anchoring. Longer dwell times often indicate sustained presence typical of home-based activities. Studies have shown that areas with higher "time-at-home" shares tend to exhibit lower rates of robbery, theft, and burglary (Bae et al., 2025; Bogomolov et al., 2015; Hipp & Kim, 2019). This indicator complements the nighttime-residency ratio by capturing actual behavior rather than residence status alone. Together, these two measures provide a behavioral portrait of who stays in the neighborhood and for how long, allowing for the estimation of local guardianship potential and social cohesion.

The proposed variables collectively provide a nuanced picture of spatiotemporal population mix at the CBG level that goes beyond size of ambient population and in and out flows. These dimensions reflect the presence, movement, and interaction of both residents and visitors, enabling the analysis of mobility patterns and their potential association with crime dynamics in Arlington.

2.2.3. *Community socioeconomic disadvantage, residential instability, and population characteristics*

Consistent with social disorganization theory, this study controls for structural factors commonly associated with neighborhood crime. Data from the 2019 American Community Survey (ACS) were used to calculate measures of concentrated disadvantage, residential instability, and ethnic heterogeneity for each CBG in Arlington, TX. Concentrated disadvantage was operationalized using a principal component analysis of four variables: (1) percentage of population living at or below 125 % of the poverty level, (2) percentage of single-mother households with children, (3) unemployment rate, and (4) percentage of households receiving supplemental security income. Residential instability was measured as the combination of the percentage of renter-occupied housing and the percentage of residents who reported living in a different residence one year ago (Sampson et al., 1997). The Blau Index (Blau, 1977) was used to estimate racial and ethnic heterogeneity. Additional controls included the percentage of residents aged 15–34, a population segment frequently linked to increased crime risk (Crum & Ramey, 2023), and population density, calculated in hundreds of residents per square mile. These variables are consistent with previous studies that have operationalized neighborhood-level social disorganization (Bae et al., 2025; Korotchenko & Semukhina, 2023; Snowden, 2019; Snowden et al., 2020).

2.2.4. *Risky places and land use*

Data on various commercial and retail businesses were sourced from ArcGIS Pro Business Analyst, the Open Texas Data Portal, the City of Arlington website, and Google Earth. The subset of commercial establishments analyzed includes restaurants, grocery stores, convenience stores, gas stations, sports complexes, and bars. Land use information was obtained through the City of Arlington website, while administrative data from the Arlington City Association of Governments (2019) were utilized to calculate the percentage of each census block group categorized into various land use classifications.

2.3. *Analytical Strategy*

The analysis proceeded in two complementary stages to assess the criminogenic relevance of SPM dimensions. In the first stage, k-means multivariate clustering was used to group Arlington's CBGs into distinct mobility profiles based on their SPM characteristics. In the second stage, generalized spatial two-stage least squares (GS2SLS) models were estimated to examine the association between these SPM profiles—or alternatively, the underlying continuous SPM facets—and crime rates, while controlling for social disorganization, land use, and spatial dependence.

Five indicators—non-resident origin counts, median travel distance, stop counts per device, median dwell time, and nighttime-resident proportion—served as the input variables for the clustering procedure. These indicators were standardized and entered into the multivariate clustering algorithm in ArcGIS Pro, which classified CBGs based on shared SPM features. The k-means method was selected for its efficiency, clarity of interpretation, and compatibility with prior studies on neighborhood classification in spatial criminology (Jain, 2010; Jiang et al., 2012). Preliminary diagnostics indicated considerable multicollinearity among the SPM variables (maximum variance inflation factor = 8.17), reinforcing the value of a clustering approach that reduces dimensionality while preserving theoretically meaningful distinctions. The resulting clusters represent holistic SPM profiles, capturing latent combinations of mobility behaviors that may correspond to distinct criminogenic environments—such as stable residential enclaves, mixed-use corridors, or high-transience entertainment zones.

To evaluate the crime implications of these profiles, the analysis employed GS2SLS regression using Stata 18. This method accounts for both spatial lag dependence and spatial error correlation, which are known to bias estimates in conventional regression models when unaddressed. In the first set of models, cluster membership (e.g., High-Transience vs. Stable-Residential) was used as a categorical predictor of logged violent, property, and drug-related crime rates. All models included controls for concentrated disadvantage, residential instability, racial/ethnic heterogeneity, population density, age structure, and land use composition, as well as spatially lagged versions of key independent variables to account for spillover effects across adjacent CBGs.

In the second set of models, each of the five SPM indicators was treated as a continuous variable. To reduce redundancy and improve construct clarity, the five indicators were grouped into two composite indices: a transient mobility pattern index (non-resident origin counts, travel distance, and stop frequency) and a residential anchoring pattern index (nighttime-resident proportion and dwell time). Principal component analysis (PCA) confirmed the factor structure of these groupings. These indices were then entered as predictors into alternative GS2SLS models to evaluate whether variation in specific SPM facets independently predicts crime, beyond the effects of overall cluster type.

This dual modeling strategy—comparing SPM clusters to their disaggregated components—enables both macro-level and dimension-specific tests of environmental criminology hypotheses. It also provides practical insights for crime prevention, allowing policymakers to distinguish between neighborhoods with similarly high population density but divergent behavioral risk profiles.

3. Results

3.1. Identified CBG multivariate clustering

To identify distinct Spatiotemporal Population Mix (SPM) profiles across Arlington's neighborhoods, k-means multivariate clustering was applied to the five behavioral indicators: non-resident origin counts, median travel distance, stop counts per device, median dwell time, and nighttime-resident proportion. These indicators jointly reflect the three theoretical SPM dimensions—visitor inflow heterogeneity, movement intensity, and residential anchoring—and were selected to classify census block groups (CBGs) based on underlying population-movement dynamics.

To determine the most appropriate number of SPM clusters, several candidate solutions were evaluated using the pseudo-F statistic, which measures between-cluster separation relative to within-cluster homogeneity. The pseudo-F statistic assesses clustering quality by measuring the ratio of variance between clusters to variance within clusters. Higher pseudo-F values indicate better clustering differentiation, with more distinct and well-separated clusters (Sinaga, Satyahadewi, & Perdana, 2023; Thorndike, 1953). The chart in Fig. 2 illustrates the pseudo-F statistic values across a range of cluster numbers. The x-axis represents the number of clusters tested, while the y-axis shows the pseudo-F statistic. To identify the optimal number of clusters, the authors examined the "elbow point"—the point at which additional clusters result in diminishing improvements in the pseudo-F statistic. From the chart, the pseudo-F statistic reaches its peak at 3 clusters (82.29), indicating the highest differentiation. While the slope begins to flatten between 3 and 5 clusters, the solution with 3 clusters is optimal as it maximizes both within-cluster similarity and between-cluster differences. Although marginal improvements continued between 3 and 5 clusters, the three-cluster solution was selected for its parsimony and interpretability in capturing discrete mobility ecologies.

The clustering procedure identified three distinct SPM profiles: Cluster 1 (Stable Residential), Cluster 2 (Moderate Mobility), and Cluster 3 (High Transience). Fig. 3 displays the spatial classification of Arlington's CBGs, while Fig. 4 presents box plots illustrating variation in SPM indicators across clusters. These profiles reflect meaningful variation in SPM facets, such as visitor origin diversity, travel distance, and temporal anchoring, and serve as the foundation for subsequent regression analyses.

Table 2 presents the distribution of the five Spatiotemporal Population Mix (SPM) indicators across the three identified clusters. Among the indicators, stop counts per device exhibited the strongest discriminating power ($R^2 = 0.823$), followed by non-resident origin counts ($R^2 = 0.715$) and median travel distance ($R^2 = 0.586$). Median dwell time and nighttime-resident proportion showed more modest cluster-level differentiation, with R^2 values of 0.418 and 0.365, respectively.

Cluster 1, labeled the Stable Residential Cluster ($n = 80$), is characterized by high levels of residential anchoring and low visitor-driven activity. On average, CBGs in this cluster had the highest nighttime-resident proportion (M = 0.585) and the longest median dwell time (M = 67.9 min), indicating that residents remained in the area for extended periods. Visitor inflow heterogeneity and movement intensity were both low: devices traveled shorter distances from home (M =

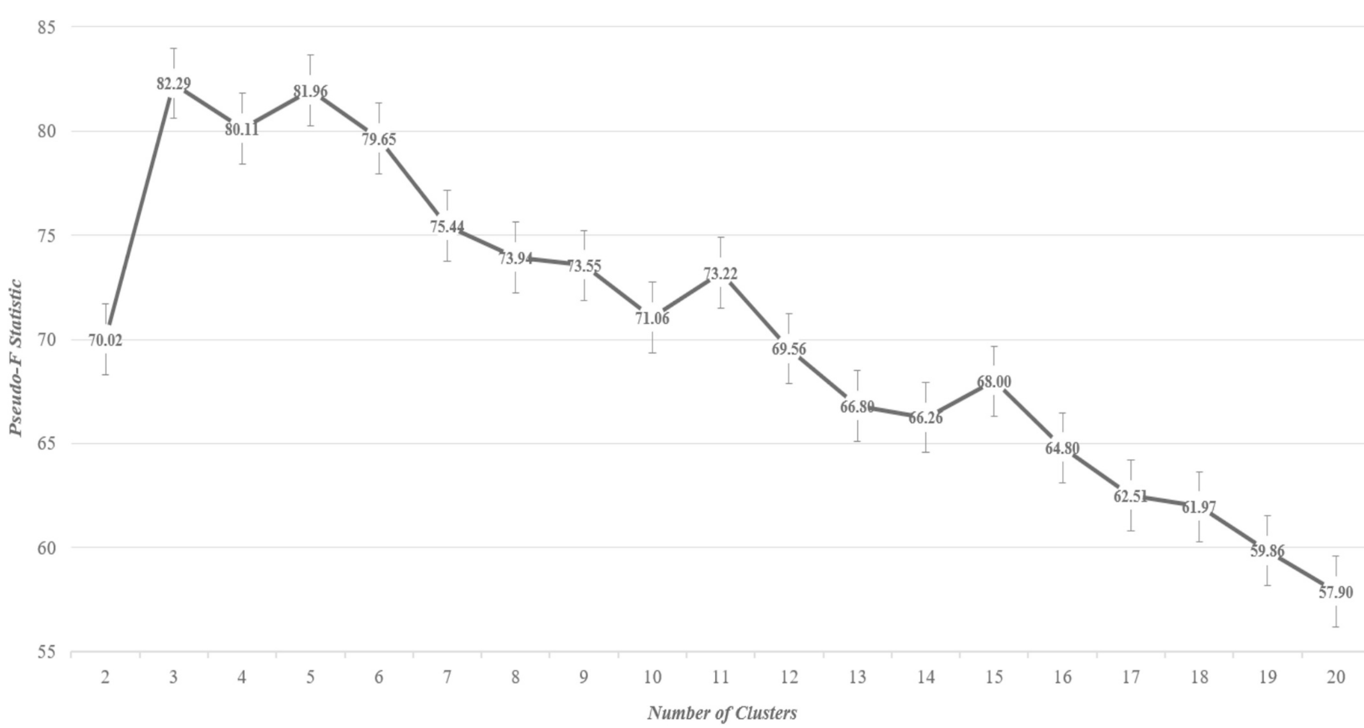

Fig. 2. Optimized Pseudo-F Statistic Chart for the "Elbow Test".

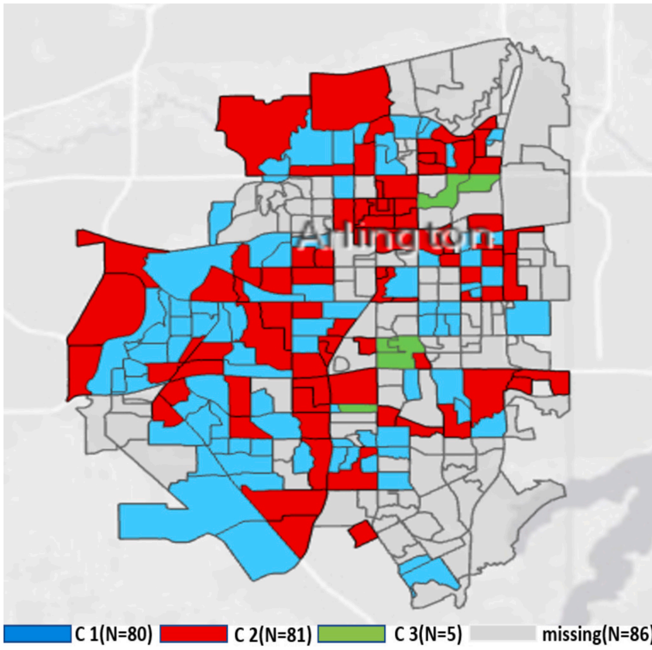

Fig. 3. A Map of Multivariate Clustering for Mobility Pattern.

622.3 m), originated from fewer distinct locations (M = 332.9 CBGs), and stopped less frequently (M = 27,025 stops per device).

Cluster 3, the High Transience Cluster (*n* = 5), reflects the opposite pattern, with indicators suggesting elevated inflow heterogeneity and transient circulation. These CBGs had the lowest nighttime-resident proportion (M = 0.490) and shortest median dwell time (M = 13.9 min), consistent with low residential anchoring. In contrast, visitor inflow was both broad and distant: devices in this cluster originated from an average of 4189.8 unique CBGs and traveled a median distance of 15,657.9 m. Movement intensity was also extremely high, with an average stop count of 387,351.8—an order of magnitude greater than in the other clusters.

Cluster 2, the Moderate Mobility Cluster (*n* = 81), exhibited intermediate values across all SPM indicators. These neighborhoods demonstrated moderate levels of inflow diversity, distance traveled, stop frequency, dwell time, and nighttime-resident proportion, suggesting a balanced mix of residential and commercial land uses.

Table 3 summarizes the sociodemographic profiles, land use compositions, and crime rates associated with each SPM cluster. The High Transience Cluster (Cluster 3) exhibits the most challenging conditions from a criminological perspective. These areas have the highest levels of concentrated disadvantage (M = 0.096) and ethnic heterogeneity (66.4 %), alongside the greatest population density (M = 2.439 hundred residents per square mile). Although small in number, these CBGs represent urbanized, commercially dense zones with elevated social disorganization risk.

In contrast, the Stable Residential Cluster (Cluster 1) displays more

Table 2
Descriptive Statistics for SPM Indicators by Cluster

SPM Indicators	R^2	Mean	Cluster 1 (mean)	Cluster 2 (mean)	Cluster 3 (mean)
Nighttime residing proportion	0.365	0.544	0.585	0.504	0.490
Median dwell time (minutes)	0.418	43.005	67.901	18.682	13.901
Distance from home (meters)	0.586	3081.215	622.314	4877.020	15,657.866
Stop counts per device	0.823	42,467.350	27,025.036	37,126.502	387,351.8
Non-resident origin counts	0.715	726.349	332.857	923.051	4189.8

Note: Cluster 1 – Stable Residential; Cluster 2 – Moderate Mobility; Cluster 3 – High Transience.

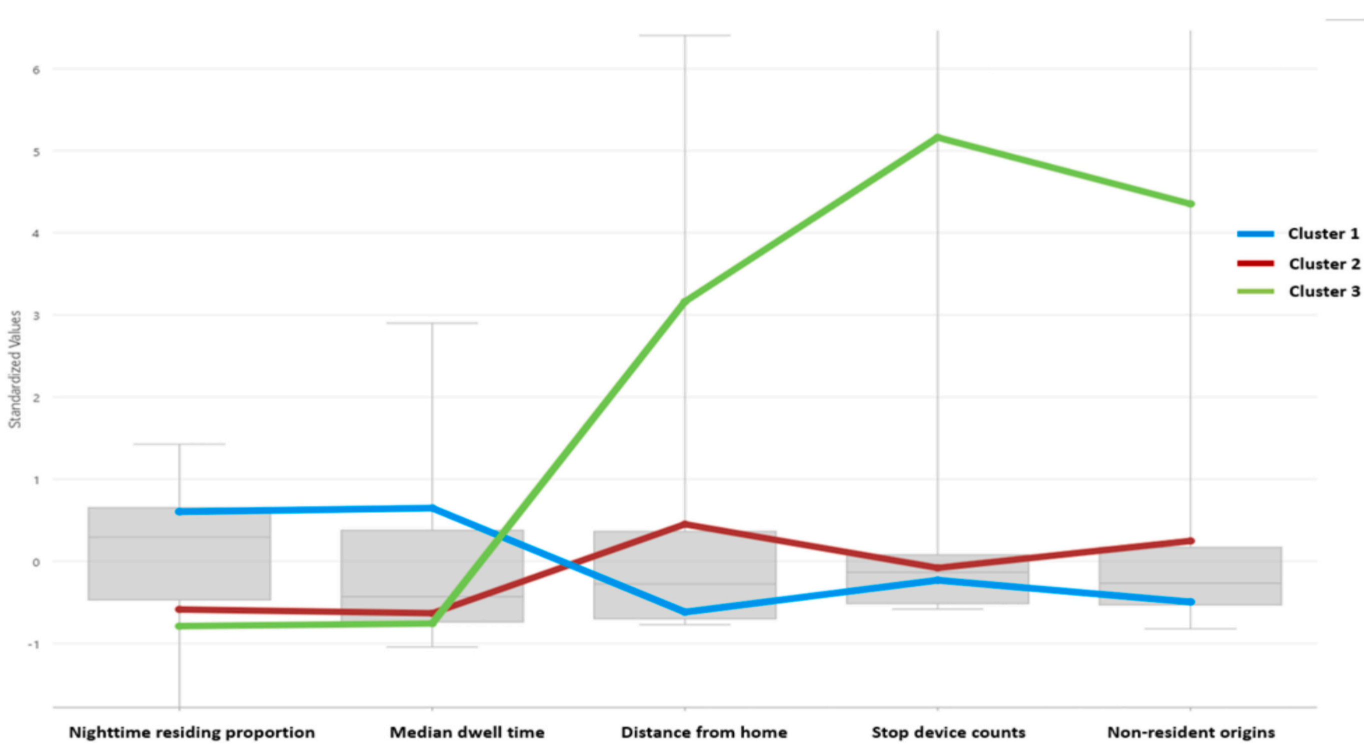

Fig. 4. Multivariate Clustering Box-Plots for Mobility Pattern Variables.

Table 3
Socio-Demographic, Land Use, and Crime Characteristics Means Across SPM Clusters

Variables	Cluster 1 (Residential Stability Cluster)	Cluster 2 (Moderate Mobility Cluster)	Cluster 3 (High Transience Cluster)
Concentrated disadvantage	0.081	0.091	0.096
Ethnic heterogeneity	54.0	54.4	66.4
Residential instability	0.132	0.161	0.131
% Aged 15 to 34	0.559	0.629	0.503
% Aged 65 and over	0.284	0.266	0.219
Population density	2.153	2.183	2.439
Bars per CBG	0.046	0.175	0.410
Gas stations per CBG	0.226	0.250	0.20
Grocery stores per CBG	0.250	0.325	0.00
Convenience stores per CBG	0.262	0.513	0.20
Restaurants per CBG	1.285	4.10	7.60
Sport complexes per CBG	0.00	0.038	0.40
% Residential	95.12	89.14	92.52
% Rented households	34.13	44.83	42.2
% Commercial/ Entertainment	0.79	2.95	3.92
% Parking space	0.07	0.18	0.43
% Park/Open space	0.31	0.44	0.57
% Vacant areas	2.54	3.64	1.43
Violent crime rate	0.372	0.556	2.685
Property crime rate	0.492	0.641	1.788
Drug-related crime rate	0.686	1.048	2.067

favorable community indicators. These neighborhoods have the highest proportion of residents aged 65 and older (28.4 %), the highest residential land use share (95.1 %), and the lowest rates of rental housing and commercial activity. Their amenity profile is consistent with low routine activity volume, featuring fewer bars (M = 0.046), restaurants (M = 1.29), and convenience-oriented retail outlets.

The Moderate Mobility Cluster (Cluster 2) lies between the two extremes. These CBGs report the highest levels of residential instability (M = 0.161) and the greatest proportion of younger residents aged 15–34 (62.9 %), consistent with areas undergoing demographic turnover or mixed-use redevelopment. Retail presence is moderate to high, with the highest density of convenience stores (M = 0.513) and grocery stores (M = 0.325) per CBG.

Crime rates vary markedly by cluster. The High Transience Cluster reported the highest rates across all three categories: violent crime (M = 2.685), property crime (M = 1.788), and drug-related crime (M = 2.067). These rates substantially exceed those observed in the other clusters, reinforcing the theoretical association between transient population flows and criminogenic conditions. Conversely, the Stable Residential Cluster recorded the lowest crime rates in every category, consistent with its strong anchoring and limited visitor inflow.

3.2. *Generalized spatial two-stage least squares estimates: cluster-based models*

To evaluate how neighborhood-level mobility profiles influence crime, generalized spatial two-stage least squares (GS2SLS) regression was employed, using SPM clusters as the primary independent variable. Separate models were estimated for logged violent crime (Model 1), property crime (Model 2), and drug-related crime (Model 3). GS2SLS accounts for spatial dependence in both the dependent and independent variables and adjusts for spatially autocorrelated error terms, offering robust estimates of local and spillover effects. Log transformation of the outcome variables mitigated skewness and stabilized variance.

The Residential Stability Cluster (Cluster 1) served as the reference category in all models. As shown in Table 4, neighborhoods in the High Transience Cluster (Cluster 3) were significantly more criminogenic across all three crime types. Compared to the reference group, these block groups recorded significantly higher rates of violent crime (b = 0.692, SE = 0.214), property crime (b = 0.499, SE = 0.156), and drug-related crime (b = 0.515, SE = 0.147). The Moderate Mobility Cluster (Cluster 2), in contrast, was associated with higher drug crime rates (b = 0.106, SE = 0.048) but did not differ significantly from Cluster 1 in terms of violent or property crime.

Several community-level predictors were also associated with elevated crime. Concentrated disadvantage significantly predicted violent crime (b = 0.075, SE = 0.027), and the proportion of residents aged 15–34 was a positive correlate of drug crime (b = 0.267, SE = 0.122). Amenity effects varied by crime type: bars and grocery stores were positively associated with violent and drug crime, whereas convenience stores predicted violent and property crime. These patterns underscore the criminogenic potential of high-activity retail environments.

Critically, spatial lag terms for the dependent variables were significant in all three models ($p < 0.001$), underscoring the importance of spatial diffusion effects—crime in a given CBG is strongly influenced by crime in adjacent areas. Spatially lagged versions of several independent variables also reached marginal or significant levels of association in the expected directions.

While the findings affirm the criminogenic significance of high-transience environments, it is important to note the small sample size of Cluster 3 ($n = 5$). Post-hoc power analyses indicated that the statistical power for detecting effects in this group falls below the conventional 0.80 threshold. Nevertheless, the decision to retain Cluster 3 in the analysis was based on theoretical relevance. High-transience neighborhoods—though rare—often exhibit distinctive social-ecological features, such as high population churn, weakened informal control, and extensive inflow from unfamiliar origins. These conditions are widely theorized in environmental criminology as key facilitators of crime (e.g., Andresen & Malleson, 2011; Brantingham & Brantingham, 1995; Hipp, 2007; Wo et al., 2024). The robust and consistent crime elevations observed in this small subset of CBGs suggest that even infrequent urban forms may exert a disproportionate impact on citywide crime distributions.

3.3. *Generalized spatial two stage least squares estimates: pca-based models*

To complement the cluster-based analysis and enhance statistical power, we conducted an alternative modeling approach using continuous measures of the Spatiotemporal Population Mix (SPM). Specifically, Principal Component Analysis (PCA) was applied to the five standardized SPM indicators: non-resident origin counts, median travel distance, stop counts per device, median dwell time, and nighttime-resident proportion. This procedure addressed multicollinearity, enabled full use of the 166-block group sample, and produced theoretically coherent composite indices for regression modeling.

PCA with Varimax rotation revealed a two-component structure that together explained 80.7 % of the total variance. As shown in Table 5, Component 1 loaded heavily on stop counts, distance from home, and origin diversity—three indicators aligned with the transient and heterogeneous nature of visitor flows. Component 2 was defined by nighttime-resident proportion and dwell time, indicators capturing stable, resident-driven occupancy patterns. All factor loadings exceeded 0.70, confirming that each variable was meaningfully represented within its respective dimension.

Based on these results, two composite indices were constructed. The Transient Mobility Pattern index reflects block groups characterized by

Table 4
Generalized Spatial Two-Stage Least Squares (GS2SLS) Models: Mobility-Based Cluster Groups and Community Crime

	Violent Crime (lg)		Property Crime (lg)		Drug Crime (lg)	
	Model 1		Model 2		Model 3	
	b	SE	*b*	SE	*b*	SE
Block group variables						
High Transience (Cluster 3)	0.692**	0.214	0.499**	0.156	0.515***	0.147
Moderate Mobility (Cluster 2)	−0.032	0.068	−0.045	0.049	0.106*	0.048
Concentrated disadvantage	0.075**	0.027	0.035†	0.020	−0.001	0.019
Residential instability	0.006	0.036	0.023	0.027	−0.0325	0.025
Ethnic heterogeneity	0.105	0.223	0.131	0.167	−0.289	0.156
% aged 15 to 34	0.177	0.174	0.248	0.131	0.267*	0.122
Population density	0.001**	0.005	0.001*	0.003	0.001	0.004
Bars	0.169†	0.081	0.059	0.061	0.137*	0.059
Gas stations	−0.043	0.057	0.036	0.041	0.046	0.039
Sports complexes	0.311*	0.150	−0.040	0.111	−0.080	0.107
Grocery stores	0.232**	0.060	0.048	0.049	0.172**	0.042
Convenience stores	0.150*	0.057	0.128**	0.044	0.068	0.006
Restaurant	0.008	0.009	0.021**	0.006	0.009	0.006
Spatially lagged variables						
High Transience (Cluster 3)	−0.534	0.706	−0.676	0.572	−0.290	0.554
Moderate Mobility (Cluster 2)	−0.335	0.202	−0.427	0.147	−0.526	0.140
Concentrated disadvantage	0.091	0.084	0.018	0.063	0.065	0.057
Residential instability	−0.079	0.104	−0.147†	0.080	0.038	0.071
Ethnic heterogeneity	0.888	0.487	0.226	0.378	0.617†	0.345
% aged 15 to 34	−0.092	0.488	0.441	0.373	−0.248	0.330
Population density	−0.393*	0.122	−0.001**	0.001	1.592	1.795
Bars	0.077	0.243	0.249	0.169	−0.119	0.157
Gas stations	−0.114	0.148	−0.146	0.109	−0.154	0.099
Sports complex	−0.782	0.405	0.308	0.311	0.047	0.271
Grocery stores	0.045	0.179	0.202	0.163	0.053	0.123
Convenience stores	−0.318	0.168	−0.097	0.139	−0.069	0.126
Restaurant	−0.004	0.026	−0.028	0.019	−0.008	0.017
Spatial lag (DV)	1.167***	0.176	1.359***	0.157	1.239***	0.151
Spatial error (DV)	-3.024†	1.585	−1.585	1.339	−5.443**	1.826
Constant	−0.058	0.190	−0.007	0.141	0.024	0.132
Wald test	$\chi2(15) = 126.41$***		$\chi2(15) = 191.52$***		$\chi2(15) = 135.41$***	

Note. N (block groups) = 166; SE = standard error; The Residential Stability (Cluster 1) as the reference group.
† $p < 0.1$
* $p < 0.05$
** $p < 0.01$
*** $p < 0.001$

Table 5
Rotated Component Matrix for SPM Indicators

Variables	Component 1	Component 2
Stop device count	0.928	−0.003
Distance from home	0.810	−0.441
Non-resident origins	0.928	−0.284
Nighttime residing proportion	−0.151	0.794
Dwell time	−0.171	0.835

high stop frequency, long-distance inflow, and diverse visitor origins—areas theorized to experience elevated crime risk due to increased offender–target convergence and guardianship dilution. The Residential Mobility Pattern index captures local anchoring through sustained presence and overnight residence, theorized to support informal control and reduce crime risk.

These indices were entered as continuous predictors into a new set of GS2SLS regression models, allowing for citywide estimation of mobility–crime associations without relying on categorical cluster membership. Using PCA in this way reduces dimensionality, resolves multicollinearity among the original indicators, and allows us to retain the full set of 166 block groups in the analysis. The next section presents the results of this analysis.

3.4. Generalized spatial two stage least squares estimates using composite mobility indices

To complement the cluster-based analysis and enhance generalizability, a second set of models used the continuous composite indicators derived from principal component analysis (PCA) as independent variables. Table 6 reports the results of three generalized spatial two-stage least squares (GS2SLS) models predicting logged rates of violent crime (Model 4), property crime (Model 5), and drug-related crime (Model 6) across the full sample of 166 census block groups in Arlington.

The two mobility indices—Transient Mobility Pattern and Residential Mobility Pattern—were entered as continuous predictors. The transient mobility index reflects high stop frequency, long-distance inflow, and diverse visitor origins, while the residential mobility index captures neighborhood anchoring through longer dwell time and a higher proportion of nighttime-residing devices.

Results show that transient mobility is positively and significantly associated with all three categories of crime. Block groups with more intense and diverse visitor inflow experienced higher rates of violent crime ($b = 0.022$, $SE = 0.007$), property crime ($b = 0.016$, $SE = 0.004$), and drug-related crime ($b = 0.007$, $SE = 0.002$). In contrast, residential mobility is negatively and significantly associated with all three outcomes. Greater residential anchoring and longer dwell times were linked to lower levels of violent ($b = -0.022$, $SE = 0.008$), property ($b = -0.013$, $SE = 0.005$), and drug-related crime ($b = -0.010$, $SE = 0.003$).

Several sociodemographic and land use controls also showed notable associations. Concentrated disadvantage was a significant predictor of

Table 6
Generalized Spatial Two Stage Least Squares (GS2SLS) Models: Examining the Impact of Transient and Residential Mobility Patterns on Community Crime

	Violent Crime (lg)		Property Crime (lg)		Drug Crime (lg)	
	Model 4		Model 5		Model 6	
	b	SE	*b*	SE	*b*	SE
Block group variables						
Transient mobility pattern	0.022**	0.007	0.016**	0.004	0.007**	0.002
Residential mobility pattern	−0.022**	0.008	−0.013*	0.005	−0.010**	0.003
Concentrated disadvantage	0.275*	0.132	0.042	0.087	−0.064	0.052
Residential instability	−0.213	0.172	−0.126	0.110	−0.040	0.068
Ethnic heterogeneity	−1.256	1.056	−0.706	0.688	0.085	0.427
% aged 15 to 34	1.018	0.851	0.757	0.546	0.152	0.336
Population density	0.001	0.001	0.001†	0.003	0.001*	0.004
Bars	0.315	0.377	0.391	0.262	0.096	0.162
Gas stations	−0.371	0.271	−0.261	0.173	0.258	0.109
Sports complex	0.940	0.714	0.944*	0.475	0.877*	0.282
Grocery stores	0.277	0.288	0.204	0.202	0.013	0.125
Convenience stores	0.162	0.263	−0.047	0.185	−0.065	0.116
Restaurant	0.008	0.041	−0.053	0.026	−0.042	0.015
Spatially lagged variables						
Transient mobility pattern	−0.019	0.019	−0.021	0.012	−0.007	0.008
Residential mobility pattern	−0.005	0.021	−0.004	0.130	−0.005	0.009
Concentrated disadvantage	−0.167	0.317	0.112	0.230	0.378*	0.161
Residential instability	−0.089	0.464	−0.010	0.286	−0.278	0.198
Ethnic heterogeneity	0.363	2.233	1.203	1.424	0.505	0.971
% aged 15 to 34	−1.252	1.983	−1.874	1.202	−0.172	0.820
Population density	−0.001†	0.001	−0.001	0.002	−0.001	0.795
Bars	1.045	0.998	0.230	0.591	0.539	0.438
Gas stations	0.637	0.655	0.395	0.394	0.656*	0.290
Sports complex	3.033	1.603	−1.994†	1.016	−2.337*	0.694
Grocery stores	−0.179	0.889	−0.487	0.528	0.559	0.356
Convenience stores	0.468	0.168	0.364	0.496	0.151	0.393
Restaurant	0.115	0.026	0.054	0.065	0.011	0.045
Spatial lag (DV)	0.935***	0.176	1.068***	0.163	0.977***	0.222
Spatial error (DV)	-6.435**	1.967	−9.508**	2.826	−4.457*	1.921
Constant	1.391	0.892	1.047	0.562	0.024	0.132
Wald test	$\chi2(15) = 38.99$***		$\chi2(15) = 74.88$***		$\chi2(15) = 49.98$***	

Note. N (block groups) = 166; SE = standard error.
† $p < 0.1$
* $p < 0.05$.
** $p < 0.01$.
*** $p < 0.001$.

violent crime (b = 0.275, SE = 0.132), while the presence of sports complexes was positively associated with property (b = 0.944, SE = 0.475) and drug-related crime (b = 0.877, SE = 0.282). Other built-environment variables such as bars, gas stations, and grocery stores exhibited mixed and model-specific associations.

Importantly, the spatial lag of the dependent variable was significant in all models ($p < 0.001$), confirming strong spatial dependence in crime outcomes. Crime rates in one CBG were influenced by crime rates in adjacent areas, consistent with prior research on spatial diffusion effects. Spatially lagged versions of some predictors, including concentrated disadvantage and presence of gas stations or sports complexes, were also significant in select models, underscoring the importance of accounting for spatial spillovers.

4. Discussion

The present study advances environmental criminology by introducing and testing two theoretically grounded behavioral constructs: the Transient Mobility Pattern, encompassing visitor inflow heterogeneity and movement intensity, and the Residential Mobility Pattern, characterized by residential anchoring. Both constructs are derived from high-resolution GPS data provided by Advan, which allows for fine-grained measurement of how people circulate, converge, and anchor in micro-geographic spaces.

Visitor inflow heterogeneity, measured by non-resident origin counts and median travel distance, captures the diversity and spatial reach of visitors. These variables reflect neighborhood-level variation in both place attractiveness and levels of offender motivation and target suitability—key mechanisms in routine activity and crime-pattern theory. Movement intensity, operationalized as stop counts per device (i.e., the ratio of total stops to unique devices), measures how frequently people pause within a space, indicating the likelihood of offender–target convergence and the potential for guardianship dilution. Residential anchoring, indicated by the proportion of devices residing in the area at night and by median dwell time, quantifies the degree to which a neighborhood is occupied by individuals with consistent overnight presence, a proxy for informal surveillance and community stability.

Unlike traditional measures of ambient population that rely on static headcounts or daytime presence alone, these dimensions emphasize not just how many people are in a location but how they use and inhabit that space. This behavioral orientation allows for direct operationalization of theoretical mechanisms such as convergence, guardianship, and place management.

In our multivariate models predicting violent, property, and drug-related crimes (Table 6), transient mobility patterns were positively and significantly associated with elevated crime rates, even after controlling for concentrated disadvantage, residential instability, population density, and risky land uses. In contrast, residential mobility patterns showed consistent negative associations with all three crime types, reinforcing the protective effect of local anchoring and sustained presence.

These findings refine our understanding of mobility-based opportunity structures for crime. Among the transient mobility indicators, stop counts per device—a proxy for how intensively people circulate within a space—proved most influential. Areas with high stop counts per device were associated with elevated crime rates, consistent with the idea that such places function both as crime generators, where routine foot traffic inadvertently produces convergence, and crime attractors, which draw motivated offenders to areas rich with unguarded targets.

Visitor inflow heterogeneity also emerged as a significant criminogenic feature. Areas drawing individuals from a wider variety of home CBGs and greater distances likely experience diminished social cohesion, reduced familiarity among occupants, and weakened informal control. These conditions may increase both victimization risk and situational offender motivation. In our principal component analysis, this facet loaded alongside movement intensity to form a single transient mobility dimension—Mobility Transiency—which was positively associated with all three crime outcomes.

By contrast, Residential Anchoring, composed of longer dwell times and a higher proportion of nighttime-residing devices, consistently suppressed crime. This dimension likely reflects stronger place attachment, routine engagement with the space, and more robust informal surveillance. While less emphasized in the cluster typology, residential mobility emerged as a consistent protective factor in the continuous-variable models, suggesting that dwell time and overnight stability should be central to environmental criminology frameworks.

Beyond individual predictors, the persistent significance of spatial lag terms across all models confirms that crime is not isolated but spreads through space—crime in one block group is influenced by crime in adjacent areas. These spatial diffusion effects reinforce the value of adopting area-wide prevention strategies, rather than narrowly targeting isolated hotspots.

The present study also demonstrates that these SPM dimensions co-occur in distinct configurations. Our cluster analysis identified three empirically meaningful neighborhood profiles. Cluster 3, the High Transience Cluster, was defined by high stop counts per device, long-distance inflow, broad origin diversity, and low residential anchoring. It aligned with entertainment and commercial districts characterized by high visitor churn, low vacancy, and a built environment oriented toward short-duration activity. Despite representing only five census block groups, this cluster consistently showed the highest crime rates in Arlington. Cluster 1, the Stable Residential Cluster, exhibited the opposite profile: low stop counts, local inflow, long dwell times, and a high proportion of nighttime-residing devices. These were predominantly residential neighborhoods with older populations and long-term occupancy.

Although the connection between crime and land use has been well established in prior literature, our results suggest that the ways people move through and interact with urban space may be even more consequential than the static presence of criminogenic facilities. In our models, land-use features such as bars, grocery stores, and sports complexes showed crime associations consistent with routine activity expectations. Notably, sports complexes—large venues generating periodic surges in visitation—were significantly associated with higher rates of property and drug-related crime, reinforcing their role as crime generators. Yet even after controlling for these features, SPM dimensions retained strong explanatory power, indicating that behavioral mobility patterns are not reducible to land use alone.

From a practical standpoint, the mobility-based framework outlined here offers an alternative lens for place-based crime prevention. In settings where up-to-date crime data are delayed or incomplete, mobility profiles could serve as leading indicators of criminogenic potential. For example, Cluster 3's small footprint—just five out of 166 CBGs—contained the highest average crime rates. This underscores how targeted patrols or environmental interventions in a few high-transience micro-areas could yield disproportionate returns. Furthermore, because the SPM measures are based on variables commonly reported by commercial mobility-data providers, this framework is replicable in other jurisdictions.

Finally, our findings offer a cautionary note regarding reliance on stationary population data and standard census-based risk factors. Although Clusters 1 and 2 had comparable population densities and similar levels of racial/ethnic heterogeneity, they exhibited markedly different crime profiles—differences that were largely explained by SPM characteristics. Similarly, Cluster 2 had slightly higher residential instability and nearly equal concentrated disadvantage relative to Cluster 3, yet experienced significantly less crime. These patterns suggest that static social disorganization indicators are insufficient on their own and that a mobility-informed view of neighborhood ecology offers a more complete picture.

5. Limitations

Several limitations of this study should be acknowledged. First, the analysis relies on secondary human mobility data provided by Advan, a commercial data vendor whose sampling framework is optimized for consumer analytics. Advan's inclusion criteria prioritize census block groups (CBGs) with at least 400 points of interest (POIs), resulting in the exclusion of 86 of Arlington's 252 CBGs. While comparative analysis in Table 1 demonstrates that the excluded areas are demographically and structurally similar to the included sample—with no evidence of spatial clustering in Fig. 1—this exclusion nonetheless restricts the generalizability of the findings to the city as a whole. Moreover, the study's sample may slightly underrepresent neighborhoods with lower levels of commercial activity or more residential character.

Second, one cluster identified in the k-means procedure—Cluster 3, the High-Transience Cluster—comprised only five CBGs. This small group size raises concerns regarding statistical power, particularly in regression models where numerous predictors are included. Although the study addresses this limitation through an alternative analytic strategy using continuous principal component indices, which retain the full sample of 166 CBGs, findings specific to the High-Transience Cluster in the categorical models should be interpreted with caution.

Third, while cellphone-based mobility data offer substantial advantages over static population proxies, they are not without limitations. Although device ownership is near-universal in the United States, adoption remains lower among certain demographic groups—particularly older adults and low-income populations (Vogels, 2021). Recent validation studies have found strong correlations between mobile device counts and census population at broader geographic scales, but weaker alignment at the CBG level (Li, Ning, Jing, & Lessani, 2024). These sampling biases, particularly for African American residents and low-income neighborhoods, may introduce modest undercoverage. However, mobile device data remain more inclusive and behaviorally rich than alternatives such as social media geotags, and their representativeness has improved over time.

Fourth, crime measurement in this study is limited to three offense categories: violent crime (robbery and aggravated assault), property crime (burglary and motor vehicle theft), and drug-related crime (possession and distribution). These categories were selected for their prevalence and analytic tractability. Future research should consider incorporating additional crime types, including lower-frequency offenses and crimes that disproportionately affect specific populations, using multi-year data to ensure sufficient statistical power at fine spatial scales.

6. Conclusion

This study contributes to environmental criminology by introducing and empirically validating the construct of Spatiotemporal Population Mix (SPM)—a multidimensional behavioral framework capturing the dynamics of how residents and visitors occupy, circulate, and anchor within micro-places. Drawing on high-resolution GPS data from mobile devices, five SPM indicators were analyzed to distinguish three theoretically salient dimensions: visitor inflow heterogeneity, movement intensity, and residential anchoring. These were used to generate both neighborhood-level clusters and continuous composite indices, each of which was evaluated in spatial regression models predicting violent, property, and drug-related crime.

The findings consistently show that transient mobility patterns—-characterized by long-distance travel, diverse visitor origins, and high stop counts per device—are positively associated with all three types of crime. In contrast, residential mobility patterns, reflecting prolonged dwell time and a high share of nighttime-residing devices, exhibit a consistent protective effect. These associations remain robust after controlling for social disorganization, population density, built environment features, and spatial dependencies. This dual approach—clustering CBGs by shared SPM profiles and separately modeling SPM facets using PCA-derived indices—demonstrates that behaviorally grounded measures of population dynamics explain variation in crime beyond what is captured by static population counts, land use, or sociodemographic context. Furthermore, the consistent significance of spatial lag terms confirms that crime is not only shaped by local conditions but also diffuses across adjacent neighborhoods, reinforcing the need for geographically coordinated prevention strategies.

From a theoretical standpoint, these findings refine key assumptions in routine activity theory, crime pattern theory, and place management theory by grounding concepts such as offender–target convergence and guardianship in directly observable mobility behaviors. Rather than assuming constant motivation or uniform exposure, SPM allows scholars to measure these mechanisms through empirical indicators of spatial churn, residential presence, and movement rhythms. Practically, the study highlights the value of integrating human mobility data into place-based crime prevention strategies. Mobility clusters—particularly those marked by high transience—can serve as leading indicators of criminogenic risk, enabling early intervention even before traditional incident-based hotspots emerge. Law enforcement agencies and urban planners may benefit from incorporating SPM metrics into resource allocation, zoning decisions, and surveillance strategies.

Future research should continue exploring how mobility patterns shape crime in different geographic settings, across different timeframes (e.g., weekdays vs. weekends), and in proximity to various risky facilities. As mobility data become more accessible and refined, criminologists have a growing opportunity to test long-standing theoretical assumptions with unprecedented spatial and temporal resolution. The present study offers a methodological blueprint for such inquiry—one that anchors environmental criminology in the behavioral fabric of everyday urban life.

CRediT authorship contribution statement

Olga B. Semukhina: Writing – original draft, Validation, Supervision, Project administration, Methodology, Funding acquisition, Conceptualization. **Junghwan Bae:** Writing – original draft, Software, Formal analysis. **Stan Korotchenko:** Writing – original draft, Conceptualization. **Chris Copeland:** Software, Methodology, Data curation.

Declaration of generative AI and AI-assisted technologies in the writing process

During the preparation of this work the author(s) used ChatGPT-4o (OpenAI, June 2025 version) to improve readability and grammar. After using this tool, the author(s) reviewed and edited the content as needed and take(s) full responsibility for the content of the publication.

References

Andresen, M. A. (2006). Crime measures and the spatial analysis of criminal activity. *British Journal of Criminology, 46*(2), 258–285.

Andresen, M. A. (2011). The ambient population and crime analysis. *The Professional Geographer, 63*(2), 193–212.

Andresen, M. A., & Jenion, G. W. (2010). Ambient populations and the calculation of crime rates and risk. *Security Journal, 23*, 114–133.

Andresen, M. A., & Malleson, N. (2011). Testing the stability of crime patterns: Implications for theory and policy. *Journal of Research in Crime and Delinquency, 48* (1), 58–82.

Bae, J., Korotchenko, S., Semukhina, O. B., & Copeland, C. (2025). Resident presence and burglary: A spatiotemporal exploration of guardianship patterns using Mobile phone tracking data as a measure of ambient population. *Crime & Delinquency, 0*(0). https://doi.org/10.1177/00111287251321443, 00111287251321443.

Barbosa, H., Barthelemy, M., Ghoshal, G., James, C. R., Lenormand, M., Louail, T., … Tomasini, M. (2018). Human mobility: Models and applications. *Physics Reports, 734*, 1–74.

Bernasco, W., & Block, R. (2011). Robberies in Chicago: A Block-level analysis of the influence of crime generators, crime attractors, and offender anchor points. *Journal of Research in Crime and Delinquency, 48*(1), 33–57. https://doi.org/10.1177/0022427810384135

Blau, P. M. (1977). *Inequality and heterogeneity: A primitive theory of social structure*. Free Press.

Bogomolov, A., Lepri, B., Staiano, J., Letouzé, E., Oliver, N., Pianesi, F., & Pentland, A. (2015). Moves on the street: Classifying crime hotspots using aggregated anonymized data on people dynamics. *Big Data, 3*(3), 148–158.

Brantingham, P., & Brantingham, P. (1995). Criminality of place: Crime generators and crime attractors. *Eur. J. on Crim. Pol'y & Rsch., 3*, 5.

Brantingham, P. L., & Brantingham, P. J. (1993). Environment, routine, and situation: Toward a pattern theory of crime. In *Routine activity and rational choice* (pp. 259–294). Routledge.

Chainey, S., & Ratcliffe, J. (2013). *GIS and crime mapping*. John Wiley & Sons.

Cohen, L. E., & Felson, M. (1979). Social change and crime rate trends: A routine activity approach. *American Sociological Review, 44*(4), 588–608.

Crum, J. D., & Ramey, D. M. (2023). Impact of extralegal and community factors on police officers' decision to book arrests for minor offenses. *American Journal of Criminal Justice, 48*(3), 572–601.

Eck, J. E., Clarke, R. V., & Guerette, R. T. (2007). Risky facilities: Crime concentration in homogeneous sets of establishments and facilities. *Crime Prevention Studies, 21*, 225.

Felson, M., & Eckert, M. A. (2018). *Crime and everyday life: A brief introduction*. Sage Publications.

Hipp, J. R. (2007). Block, tract, and levels of aggregation: Neighborhood structure and crime and disorder as a case in point. *American Sociological Review, 72*(5), 659–680.

Hipp, J. R., & Kim, Y.-A. (2019). Explaining the temporal and spatial dimensions of robbery: Differences across measures of the physical and social environment. *Journal of Criminal Justice, 60*, 1–12.

Jain, A. K. (2010). Data clustering: 50 years beyond K-means. *Pattern recognition letters, 31*(8), 651–666.

Jiang, S., Ferreira, J., & González, M. C. (2012). Clustering daily patterns of human activities in the city. *Data Mining and Knowledge Discovery, 25*, 478–510.

Korotchenko, S., & Semukhina, O. (2023). Crime, Space, and Race: A Spatial Analysis of Assaults with Victim Race and Residence as Predictors. *Crime & Delinquency. Advance online publication.*. https://doi.org/10.1177/00111287221150178

Krivo, L. J., & Peterson, R. D. (2000). The structural context of homicide: Accounting for racial differences in process. *American Sociological Review*, 547–559.

Li, Z., Ning, H., Jing, F., & Lessani, M. N. (2024). Understanding the bias of mobile location data across spatial scales and over time: A comprehensive analysis of SafeGraph data in the United States. *PLoS One, 19*(1), Article e0294430.

Malleson, N., & Andresen, M. A. (2015). The impact of using social media data in crime rate calculations: Shifting hot spots and changing spatial patterns. *Cartography and Geographic Information Science, 42*(2), 112–121.

Malleson, N., & Andresen, M. A. (2016). Exploring the impact of ambient population measures on London crime hotspots. *Journal of Criminal Justice, 46*, 52–63.

Mazerolle, L., Wickes, R., & McBroom, J. (2010). Community variations in violence: The role of social ties and collective efficacy in comparative context. *Journal of Research in Crime and Delinquency, 47*(1), 3–30.

Peterson, R. D., & Krivo, L. J. (2010). *Divergent social worlds: Neighborhood crime and the racial-spatial divide*. Russell Sage Foundation.

Ratcliffe, J. H. (2004). The hotspot matrix: A framework for the spatio-temporal targeting of crime reduction. *Police Practice and Research, 5*(1), 5–23.

Sampson, R. J., & Raudenbush, S. W. (1999). Systematic social observation of public spaces: A new look at disorder in urban neighborhoods. *American Journal of Sociology, 105*(3), 603–651.

Sampson, R. J., Raudenbush, S. W., & Earls, F. (1997). Neighborhoods and violent crime: A multilevel study of collective efficacy. *Science, 277*(5328), 918–924.

Sinaga, S. J., Satyahadewi, N., & Perdana, H. (2023). Determining the optimum number of clusters in hierarchical clustering using Pseudo-F. *Euler: Jurnal Ilmiah Matematika, Sains dan Teknologi, 11*(2), 372–382.

Snowden, A. J. (2019). Exploring violence_ The role of neighborhood characteristics, alcohol outlets, and other micro-places. *Social Science Research, 82*, 181–194.

Snowden, A. J., Hockin, S., & Pridemore, W. A. (2020). The neighborhood-level association between alcohol outlet density and female criminal victimization rates. *Journal of interpersonal violence, 35*(15-16), 2639–2662.

Sutton, P. C., Elvidge, C., & Obremski, T. (2003). Building and evaluating models to estimate ambient population density. *Photogrammetric Engineering & Remote Sensing, 69*(5), 545–553.

Thorndike, R. L. (1953). Who belongs in the family? *Psychometrika, 18*(4), 267–276.

U.S. Census, B. (2020). Quick Facts. Retrieved from https://www.census.gov/quickfacts/arlingtoncitytexas.

Vogels, E. (2021). Digital divide persists even as Americans with lower incomes make gains in tech adoption. https://www.pewresearch.org/short-reads/2021/06/22/digital-divide-persists-even-as-americans-with-lower-incomes-make-gains-in-tech-adoption/.

Weisburd, D., Groff, E., & Yang, S.-M. (2012). *The criminology of place : Street segments and our understanding of the crime problem*. Oxford University Press. https://doi.org/10.1093/acprof:oso/9780195369083.001.0001

Wo, J. C., Rogers, E. M., Berg, M. T., & Koylu, C. (2024). Recreating human mobility patterns through the lens of social media: Using twitter to model the social ecology of crime. *Crime & Delinquency, 70*(8), 1943–1970.

Wortley, R., & Townsley, M. (2016). Environmental criminology and crime analysis: Situating the theory, analytic approach and application. In *Environmental criminology and crime analysis* (pp. 20–45). Routledge.