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Resident Presence and Burglary: A Spatiotemporal Exploration of Guardianship Patterns Using Mobile Phone Tracking Data as a Measure of Ambient Population

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Abstract

This study examines the routine activity theory's capable guardianship concept using contemporary GIS data. Leveraging high-frequency geotracked mobile phone data from Advan, which provides ambient population counts for census block groups every 2 hr, the research tests the impact of residents' presence on burglary frequency at different times of the day and week. Through a series of negative binomial regression and GS2SLS models, significant variations in deterrence provided by such capable guardianship are revealed across different times of the day, as well as between weekdays and weekends. Highlighting the novelty and utility of mobile phone tracking data, the research offers insights into the temporal dynamics of residential

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burglary, informing targeted crime prevention strategies, enhancing community safety, and advancing criminological theory.

Keywords
capable guardianship, burglary, mobile phone tracking, human mobility data, spatial analysis

What can mobile phones say about ambient population and crime? In criminology, it is widely accepted that, for a fluid phenomenon like crime, the number of people present in an area often holds greater significance than the size of the residential population. Recent advancements in GIS technology have opened new avenues for criminological research into topics previously considered well-explored (Andresen, 2006; Andresen & Jenion, 2010; Malleson & Andresen, 2015). Early efforts to measure ambient population relied on sources such as geotagged social media posts and satellite imagery for estimating population density and movement patterns in public spaces (Ghosh et al., 2013; H. Zhou et al., 2021). However, the precision of GIS-based human mobility data now allows researchers to track ambient population changes more accurately using continuous mobile device data (Okmi et al., 2023; Palmer et al., 2013). Studies utilizing this data have demonstrated its critical value in shaping crime prevention strategies and improving our understanding of crime patterns (Xu et al., 2018). Recognizing the role of ambient population in shaping crime patterns, this study narrows its focus to residential burglary, a crime with significant social and economic implications.

Residential burglary has long been a concern for law enforcement and policymakers, impacting individuals' sense of security and community well-being (Kuroki, 2013). According to the Federal Bureau of Investigations' Uniform Crime Reporting (UCR) data, burglaries constitute approximately 16% of all property crimes, resulting in nearly $3 billion in property losses annually (FBI, 2019). Beyond financial harm, burglary often leaves lasting psychological effects on victims, including increased anxiety and diminished quality of life (Beaton et al., 2000; Kunst & Hoek, 2024).

Traditionally, burglary prevention strategies have been rooted in routine activity theory (RAT), which emphasizes three key components: motivated offenders, suitable targets, and capable guardians (Cohen & Felson, 1979). Capable guardianship highlights the role of individuals whose presence can deter potential offenders (Hollis-Peel & Welsh, 2014; Hollis-Peel et al., 2011). Historically, measures of capable guardianship have included neighborhood watch programs and police patrols (Reynald, 2011). However, the widespread mobile phone use presents a unique opportunity to measure guardianship in a more granular and accurate way. Mobile phone data enables researchers to track people's movement at unprecedented levels of precision (Wang et al., 2018), enhancing the understanding of how residents' presence can deter crime.

This study expands upon RAT by leveraging geo-tracked mobile phone data to examine the effect of residents' presence on residential burglary. It investigates the impact of residents' presence during different times of the day—such as breakfast, lunch, work hours, and evenings—and across weekdays and weekends. Using census block groups (CBGs) as the unit of analysis, this study provides localized insights into the temporal dynamics of capable guardianship (Andresen et al., 2017).

To guide this investigation, the study investigates two research questions. First, is there an association between the proportion of residents who stay home and residential burglaries? If so, does this association vary by time of day and day of the week?

This research is significant for its innovative use of mobile phone tracking data to measure guardianship, offering a dynamic and responsive approach that surpasses static data sources like census data or crime reports (Chen & Rafail, 2020). By examining temporal patterns in resident presence and burglary risk, this study provides actionable insights for developing targeted interventions that enhance guardianship during vulnerable periods, leading to more effective resource allocation and improved community safety.

Literature Review

Routine Activity Theory

Formulated by Cohen and Felson (1979), routine activity theory (RAT) explains crime occurrence through the convergence of three key elements: motivated offenders, suitable targets, and the absence of capable guardians (Cohen & Felson, 1979; Felson, 1995). Unlike offender-focused theories, RAT emphasizes how environmental circumstances facilitate crime, suggesting that offenses occur when a motivated offender encounters a suitable target without adequate guardianship (Clarke & Felson, 2017; Felson & Cohen, 1980). While RAT does not address why individuals become motivated offenders (Eck & Clarke, 2019; Felson, 2006), it identifies suitable targets as people, objects, or places perceived as vulnerable or valuable (Felson, 2006).

Capable guardianship is central to RAT and refers to the presence of individuals or entities that deter crime by increasing offenders' perceived risk of apprehension (Felson, 1995; Hollis-Peel et al., 2011; Reynald, 2011).

Guardianship takes both formal forms, such as law enforcement, and informal forms, such as vigilant neighbors and passersby (Felson, 2006; Sampson et al., 1997; Sherman et al., 1989). Effective guardianship discourages criminal behavior by fostering surveillance and intervention potential (Felson & Boba, 2010; Hollis-Peel et al., 2011; Reynald, 2011). However, mere presence is insufficient; effective guardianship depends on availability, capability, and willingness to act, which can be shaped by social cohesion and contextual factors—these dimensions collectively determine guardianship intensity, highlighting that not all forms of presence deter crime equally (Reynald, 2011). Research shows that capable guardianship significantly reduces crime rates by disrupting the convergence of offenders and targets (Felson, 2006; Sherman et al., 1989).

Traditional approaches to measuring guardianship have emphasized law enforcement, neighborhood watch programs, and technological tools like CCTV and alarm systems, all of which enhance vigilance and informal social control (Braga & Clarke, 2014; Sherman & Weisburd, 1995; Weisburd et al., 2014). Such initiatives are consistently linked to lower property crime rates, including residential burglary (Braga & Clarke, 2014; Felson & Eckert, 2018).

Capable Guardianship and Residential Burglary

Residential burglary is a particularly relevant focus for studying guardianship, as it directly impacts victims' sense of security and community trust. Capable guardians—whether vigilant neighbors, security systems, or regular police patrols—have been shown to deter burglars (Armitage, 2013; Tseloni et al., 2004, 2018). Homes equipped with alarm systems or visible signs of occupancy, such as lights left on, are less likely to be targeted (Tseloni et al., 2018). Additionally, neighborhoods with higher levels of social cohesion and informal surveillance often experience fewer burglaries (Reynald, 2011; Sampson et al., 1997; Skogan, 1992). These studies show that such indicators like neighborhood watch participation, visible activity, and social connections among residents enhance guardianship by increasing perceived risks for potential offenders.

Existing studies on resident presence and guardianship in burglary risk primarily examine neighborhood-level dynamics, such as visible activity and informal social control (e.g., Garofalo, 1981; Reynald, 2011). Research consistently demonstrates that active guardianship prevents crime by disrupting the convergence of offenders and targets (Hollis-Peel et al., 2011; Reynald, 2011). However, these studies have focused on community-level measures, such as passersby or neighborhood surveillance, rather than exploring how individual residents within their homes act as capable guardians. Moreover, proxies for resident presence, like visible activity, may not accurately reflect actual occupancy, further limiting prior research.

Recent advancements in data availability offer dynamic ways to measure population changes. Social media platforms like Twitter and Foursquare have been used to study ambient populations and their relationship to crime (Cheng et al., 2011; Cranshaw et al., 2012; X. Zhou & Xu, 2017). Geotagged Twitter posts, for example, have been employed to analyze neighborhood-level population fluctuations and crime patterns (Hipp et al., 2019). Other approaches, such as using satellite imagery (Ghosh et al., 2013) or Google Street View (H. Zhou et al., 2021), provide additional insights. However, these methods are constrained by limitations such as participation bias in social media data, incomplete temporal coverage, or insufficient spatial resolution. Such constraints make these sources less effective for studying resident presence within individual dwellings.

This study addresses these gaps by leveraging mobile phone GPS data to capture continuous, real-time, and highly granular measurements of resident presence within their homes. By analyzing the proportion of residents at home across 2-hr intervals, 7 days a week, throughout 2019, this research provides a dynamic and precise measure of guardianship. This granularity allows for identifying nuanced patterns in burglary risks and guardianship effectiveness that prior research, limited by static or infrequent data sources, could not address. These insights advance the understanding of routine activity theory in the context of residential burglary and offer actionable intelligence for data-driven crime prevention strategies and resource allocation.

Temporal Variations in Crime and Guardianship

Temporal variations in crime and guardianship are well-documented in criminological research. Studies have consistently shown that residential burglary rates tend to peak during daytime hours, particularly mid-morning and early afternoon, when residents are more likely to be away from home at work or school. These patterns align with the reduced availability of capable guardianship during these times (Felson, 1995; Groff & La Vigne, 2002). Conversely, burglary rates decrease during evening and nighttime hours, when home occupancy increases, and residents are more likely to engage in routine activities that enhance guardianship (Groff & La Vigne, 2002; Tseloni et al., 2018). The heightened presence of residents during these periods has been linked to increased vigilance and informal social control, which deter potential offenders (Ratcliffe, 2002; Van Wilsem, 2009).

Temporal variations also extend to differences between weekdays and weekends. Weekday routines, which often involve residents leaving their homes for work or school, create opportunities for burglary. In contrast, weekends are characterized by greater social interactions and recreational activities, which can enhance informal guardianship. For example, studies have noted lower burglary rates during weekend evenings, a trend attributed to stronger informal social controls and visible activity in neighborhoods (Bernasco & Block, 2009; Felson & Poulsen, 2003). These findings underscore the dynamic relationship between routine activities, guardianship, and crime patterns.

Despite these advancements, much of the existing research has relied on aggregate timeframes, such as day versus night or weekdays versus weekends, to examine temporal variations in guardianship. These broader categories, while informative, lack the granularity necessary to uncover nuanced patterns in guardianship effectiveness. Emerging data sources, such as mobile phone GPS data, provide a novel opportunity to overcome these limitations. Unlike traditional measures, such as census data or proxies for resident presence, mobile phone data allows for continuous, real-time tracking of population presence at finer temporal scales. This study builds on this methodological innovation by examining burglary risks using 2-hr time increments across an entire year. Analyzing such granular data enables a deeper exploration of how guardianship effectiveness fluctuates throughout the day and week, providing insights that were previously unattainable due to data limitations (Isaacman et al., 2011; Wang et al., 2018).

RAT provides a theoretical framework for understanding these temporal dynamics. Changes in daily and weekly routines affect the convergence of motivated offenders, suitable targets, and capable guardians. Offenders often exploit the predictability of routine activities to identify periods of low guardianship, making certain times of day or week more vulnerable to crime (Clarke, 1995; Felson, 1995). Conversely, non-working hours increase the likelihood of residents being present, enhancing guardianship and reducing burglary opportunities (Groff & La Vigne, 2002; Sherman et al., 1989). By leveraging high-frequency mobile phone data, this study contributes to the literature by providing an unprecedented level of temporal precision in testing RAT. This approach not only fills a critical gap in the understanding of guardianship dynamics but also offers actionable insights for developing time-specific crime prevention strategies.

Methods

Study Area

This study focuses on Arlington, Texas, a city with a population of 394,266 and a density of 4,112.7 people per square mile (U.S. Census Bureau, 2020).

Located between Dallas and Fort Worth, Arlington serves as a commuter hub, making residents' presence particularly relevant in the context of residential burglaries. The availability of detailed address-level crime data from the Arlington Police Department for 2019 further justifies its selection. Using 2019 data avoids the confounding effects of the COVID-19 pandemic, which began in 2020 and disrupted crime patterns.

Arlington's moderate urban density offers a generalizable setting for spatial crime analysis. The city features nearly equal representation of two major racial and ethnic minority groups: Hispanics (29.7%) and African Americans (22.7%), who predominantly reside in the east and south, respectively, while Whites (38.6%) are concentrated in western areas adjacent to a large lake (U.S. Census Bureau, 2020). Land use patterns in Arlington provide a strong basis for this study, with single-family residences occupying 44% of the city's land, compared to only 4.88% for multifamily residences (Arlington Open Data Center, 2025). Residential areas are primarily located on the city's fringes, whereas commercial and industrial zones are concentrated centrally and to the east.

The geographic unit of analysis is the Census Block Group (CBG), the second-smallest unit used by the U.S. Census Bureau. CBGs provide a balance between spatial granularity and access to demographic controls, which are unavailable at the smaller census block level. Smaller geographic units like CBGs capture local variations in crime and social dynamics more effectively than larger units, such as zip codes or tracts (Weisburd et al., 2014, 2015). Prior research highlights the value of CBGs in examining micro-level crime patterns and environmental influences (Hipp & Williams, 2020). For this study, using CBGs facilitates the integration of detailed demographic data into the analysis of burglary risk, allowing for a comprehensive investigation of spatial and social factors.

Measures and Data Sources

Human Mobility Data. To examine the relationship between capable guardianship and burglary risk, this study employs mobile device GPS data as a proxy for residents' presence in their homes. Mobile device data provide a dynamic, temporally precise measure of human mobility, offering significant advantages over traditional static datasets like census records or survey data. These data enable granular analyses of how residential presence varies across time and space, allowing for a robust operationalization of the capable guardianship concept within RAT.

The data for this study were obtained from Advan,[1] a leading analytics company specializing in location-based datasets. Advan collects mobile

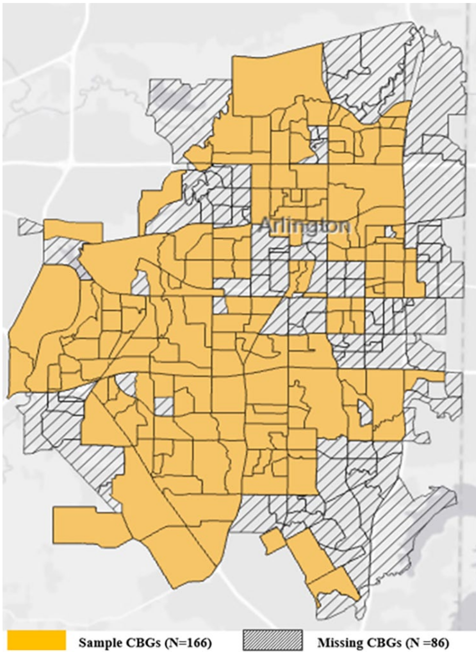

Figure 1. Geographic distribution of sampled and missing Census Block Groups (CBGs).

device GPS data aggregated at the CBG level, tracking movements based on users' interactions with mobile applications. The data include information about locations visited, origins, visitation times, and durations, offering a detailed picture of mobility patterns. Unlike other providers, which often focus on points of interest (POIs), Advan also calculates monthly foot traffic patterns aggregated across CBGs. In late 2022, Advan acquired SafeGraph's "Human Mobility Patterns" business license, integrating SafeGraph's POI geometries while refining mobility estimators.[2]

Advan's focus on marketing applications introduces a limitation: CBGs with fewer than 1,000 POIs or census block tracts with fewer than 400 POIs are excluded from the dataset. For Arlington, this results in the omission of 86 out of 252 CBGs. Figure 1 illustrates the spatial distribution of missing and included CBGs, showing no significant spatial clustering of excluded CBGs within the city.

Table 1. Descriptive Statistics of Home Capable Guardian Proportion and Burglary for a Specific Time Period.

	Sample CBGs (*N* = 166)		Missing CBGs (*N* = 86)	
Independent variables	*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 15–34	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	1,627.644	541.13	1,346.278	456.24
Median household income	75,135	1,098	73,012	1,301
% 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

To assess potential biases introduced by the exclusion of these 86 CBGs, Table 1 compares socio-economic and demographic characteristics between the included (Sample) and excluded (Missing) CBGs. Key indicators suggest that the two groups are largely comparable. For instance, concentrated disadvantage (Sample: $M=0.224$; Missing: $M=0.213$) and residential instability (Sample: $M=0.188$; Missing: $M=0.173$) show minor differences. Educational attainment (bachelor's degree: Sample=33.9%; Missing=31.1%) and median household income (Sample=$75,135; Missing=$73,012) are also closely aligned. Additionally, both the missing and sample CBGs exhibit similar percentages of residential land use.

Nevertheless, the sample includes a slightly 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 differences suggest that the study may underrepresent African-American populations to some extent. However, the overall alignment of

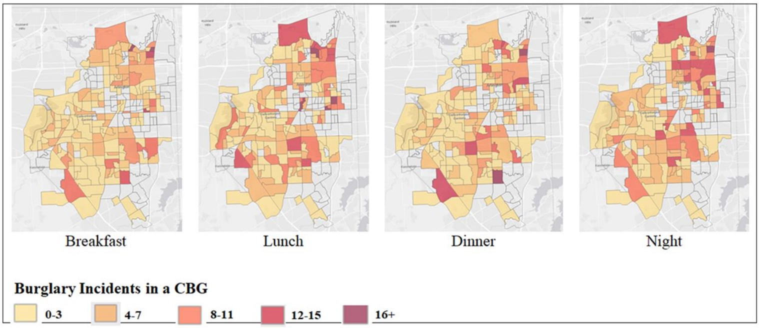

Figure 2. Maps for burglary distribution for breakfast, lunch, dinner, and night in Arlington, TX.

socio-economic characteristics across the two groups indicates minimal bias in the dataset.

Dependent Variable: Burglary Frequency. The dependent variable, burglary frequency, was measured using address-level data from the Arlington Police Department for 2019. The dataset included 1,291 incidents classified as "burglary of habitation" under the Uniform Crime Reporting (UCR) system, consistent with Texas Penal Code Sections 30.02(c)(2) and 30.02(d). These incidents were geocoded using ArcGIS Pro and aggregated at the CBG level, achieving a match rate of 95.2% across the 166 included CBGs.

Temporal patterns in burglary incidents were analyzed by aligning the reported date and time of each offense with Advan mobility data across predefined time periods, such as breakfast, lunch, dinner, night, work hours, and after-work hours. Figures 2 and 3 provide spatial representations of burglary distributions during these periods. For example, burglary incidents during weekdays were more concentrated in the northern CBGs, whereas weekend burglaries were primarily located in east-south areas. These variations reflect temporal changes in guardianship and routine activities within Arlington.

Independent variable: Capable Guardian Measure. The independent variable, capable guardianship, was operationalized as the proportion of residents staying home within each Census Block Group (CBG). Advan identifies a device's "home" based on its most frequent nighttime location (6 p.m. to 7 a.m.) over a 6-week period. The home capable guardianship proportion was calculated using the formula:

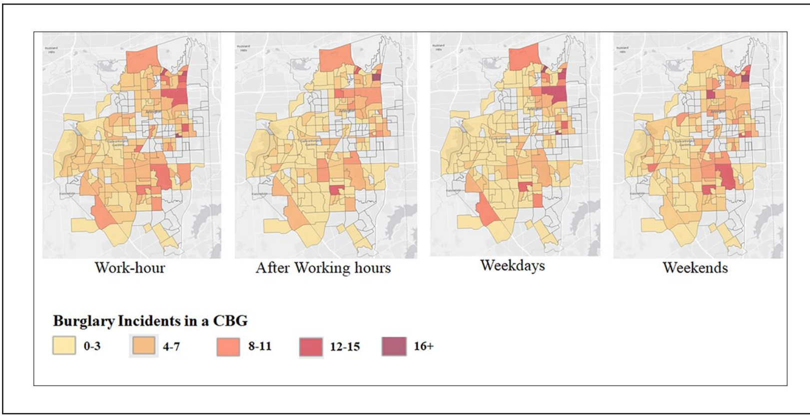

Figure 3. Maps for burglary distribution for work-hour, after work-hour, weekdays, and weekends in Arlington, TX.

$$Home\,capable\,guardian\,proportion = \frac{\sum_{1}^{H} H}{\sum_{1}^{H} H + \sum_{1}^{V} V}$$

where H represents the number of devices observed in their home CBG, and V represents the number of devices visiting the CBG but residing elsewhere. This calculation was performed across predefined time periods provided by Advan, including breakfast (6:00 a.m. to 10:59 a.m.), lunch (11:00 a.m. to 2:59 p.m.), dinner (5:00 p.m. to 8:59 p.m.), night (9:00 p.m. to midnight), work hours (7:30 a.m. to 5:30 p.m.), after-work hours (5:31 p.m. to midnight), weekdays, and weekends.

Figures 4 and 5 illustrate the spatial distribution of home capable guardianship proportions across Arlington. Suburban areas on the city's fringes generally exhibited higher proportions of home guardians, likely due to factors such as flexible work schedules or the presence of stay-at-home caregivers. Conversely, the city center displayed lower proportions, reflecting denser housing areas where residents are more likely to commute to work. These patterns underscore the importance of granular, time-specific data in understanding guardianship dynamics.

Control Variables. Control variables were derived from the 2019 American Community Survey (ACS) for Arlington's CBGs to account for socio-structural factors informed by social disorganization theory. Spatial principal

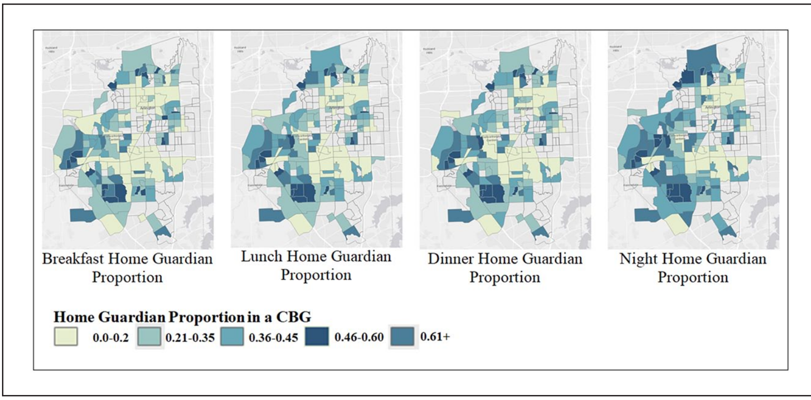

Figure 4. Maps for home capable guardian proportion for breakfast, lunch, dinner, and night in Arlington, TX.

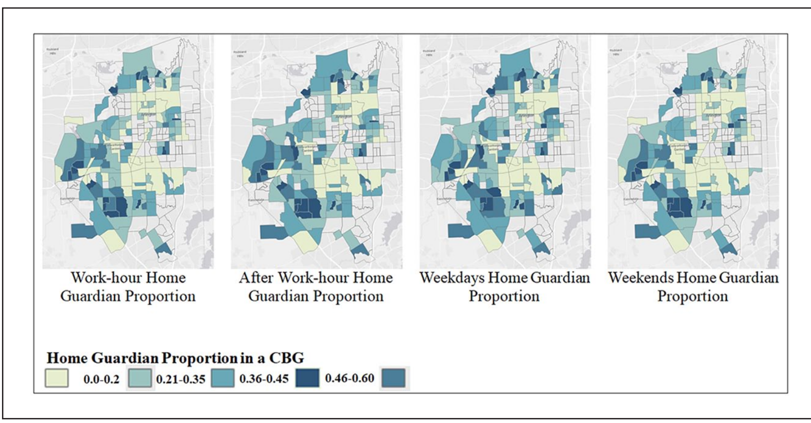

Figure 5. Maps for home capable guardian proportion for work-hour, after work-hour, weekdays, and weekends in Arlington, TX.

component analysis (PCA) was used to construct a measure of neighborhood concentrated disadvantage. This measure included the percentage of households at or below 125% of the poverty level, the percentage of single-mother households with children, the unemployment rate, and the percentage of households receiving Supplemental Security Income (Peterson & Krivo, 1999; Sampson et al., 1997).

Residential instability was measured as the percentage of rental households and the percentage of residents who had moved within the past year.

Racial and ethnic diversity within CBGs was captured using the Blau index, which reflects the distribution of residents across racial and ethnic categories, including Asian, Black, Hispanic, White, and other groups (Blau, 1977). These variables align with previous research operationalizing neighborhood-level social disorganization (Korotchenko & Semukhina, 2024; Snowden, 2019; Snowden et al., 2020; Semukhina et al., 2024).

Demographic controls included the proportion of residents aged 15 to 34, a group often associated with higher crime rates (Crum & Ramey, 2023), and the percentage of residents over 65, who may enhance guardianship due to increased home presence. The percentage of homes constructed prior to 1960 was also included to account for vulnerabilities in older residences, such as outdated security features or deteriorating entry points (Hipp, 2007; Hipp & Kim, 2019).

Additional variables included the number of residential housing units per CBG, which provided a direct measure of potential burglary targets, and population density (in hundreds per square mile) to capture the influence of urban density on crime dynamics. Collectively, these control variables allowed for a comprehensive assessment of socio-structural characteristics influencing residential burglary risk.

Analytic Strategy

Addressing Spatial Dependence. Spatial dependence, where values in one location are influenced by neighboring locations, was a critical consideration for this analysis. Such dependence often violates the independence assumption of ordinary least squares (OLS) regression (Allison, 1999). Crime and place studies frequently show that socio-ecological factors in one neighborhood can diffuse and affect crime rates in adjacent neighborhoods (Boivin & Felson, 2018; Wo et al., 2024).

To address this, spatial lag measures were constructed for independent variables using queen contiguity-based spatial weights. These weights define a neighborhood as all Census Block Groups (CBGs) that share a boundary with the focal CBG. The spatial lag measure for each independent variable reflects the average level of the variable in neighboring block groups, thereby accounting for the influence of surrounding areas. Prior to constructing spatial lag measures, spatial principal component analysis (PCA) was employed using GeoDa to create key social disorganization factors, including neighborhood concentrated disadvantage and residential instability. Racial heterogeneity was calculated using the Blau index, which quantifies diversity based on the distribution of racial and ethnic groups within each CBG (Blau, 1977). These measures were integrated into the model to account for the spatial diffusion of socio-structural characteristics and their potential impact on residential burglary rates.

Negative Binominal Regression. The dependent variable, residential burglary frequency, exhibited overdispersion, with the variance significantly exceeding the mean. As such, Negative Binomial Regression (NBR) was selected as the primary analytical technique, performed using Stata 18 software. NBR is well-suited for count data with overdispersion, as it introduces a parameter (α) to account for unobserved heterogeneity among observations (Long et al., 2021).

To ensure that NBR was the most appropriate modeling approach, diagnostic checks were conducted to compare its performance against Zero-Inflated Negative Binomial (ZINB) models, which are designed to handle excess zeros. The Vuong test (Vuong, 1989), which evaluates model fit, indicated no significant improvement with the ZINB model. This result suggests that the excess zeros in the burglary dataset did not require special handling beyond what NBR provides. Consequently, NBR was chosen for its ability to address overdispersion while maintaining model simplicity.

The general form of the estimated model is as follows:

$$Y2019 = \mathrm{B}_1 T2019 + B_2 WT2019 + B_3 S2019 + B_4 WS2019 + B_5 WY2019 + \alpha$$

where Y is the number of burglaries in the block group for 2019, T is a matrix of the home capable guardianship measure in the CBG for 2019, WT is a matrix of spatially lagged home capable guardianship measures in CBG for 2019, S is a matrix of additional independent variables (e.g., social disorganization factors, residential population characteristics and population density) in the CBG in 2019, WS is a matrix of spatially lagged control variables in the CBG in 2019, *WY is* a matrix of spatially lagged burglary incidents for CBG, and α is the intercept. Separate models were estimated for each time period available (be breakfast, lunch, evening hours, work hours, after hours, daytime, and nighttime) to evaluate the association between home capable guardianship and burglary at different times of day and across weekdays and weekends.

To evaluate multicollinearity, Variance Inflation Factor (VIF) analysis was performed on all independent variables. The VIF values for all variables were below 10, with a mean VIF of 1.77, indicating no significant multicollinearity concerns. In general, a VIF below 5 is considered an acceptable threshold (Allison, 1999). These results confirm that the independent variables, including social disorganization factors, demographic characteristics, housing

Table 2. Descriptive Statistics of Home Capable Guardian Proportion and Burglary for a Specific Time Period.

Period	Home capable guardian proportion		Burglary	
	M	*SD*	*M*	*SD*
Breakfast	0.162	0.117	1.054	1.699
Lunch	0.129	0.101	0.915	1.208
Dinner	0.127	0.090	0.813	1.142
Night	0.406	0.173	1.494	1.808
Workhour	0.097	0.080	2.217	2.711
After workhour	0.171	0.112	2.530	2.802
Weekdays	0.082	0.066	3.693	4.101
Weekends	0.118	0.076	1.121	1.361

Note. N (block groups) = 166. *M* = mean; *SD* = standard deviation.

conditions, and guardianship measures, do not exhibit problematic levels of correlation, ensuring the reliability of the model estimates.

Results

Descriptive Statistics

Table 2 presents the descriptive statistics for the home capable guardian proportion and burglary frequency across all analyzed time periods. Among the specific time periods, the nighttime hours exhibit the highest proportion of home capable guardians at the CBG level (M=0.406, SD=0.173). As expected, the proportion of home capable guardians is greater during the after-work hours (M=0.171, SD=0.112) compared to the work hours (M=0.097, SD=0.080). Similarly, weekends show a higher proportion of home capable guardians (M=0.118, SD=0.076) than weekdays (M=0.082, SD=0.066).

The average frequency of burglaries at the CBG level also varies by time period. Among the specific time intervals—breakfast, lunch, dinner, and nighttime—the nighttime period has the highest average number of burglaries (M=1.494, SD=1.808), while the dinner period has the lowest (M=0.813, SD=1.143). Across broader periods, more burglaries occur after work hours (M=2.530, SD=2.802) compared to work hours (M=2.217, SD=2.711). Additionally, weekdays see a higher average burglary frequency (M=3.693, SD=4.101) compared to weekends (M=1.121, SD=1.361).

Table 3. Descriptive Statistics of Control Variables.

Control variables	*M*	*SD*	Min	Max
Concentrated disadvantage	0.224	0.111	0.070	0.600
Residential instability	0.188	0.126	0.012	0.499
Ethnic heterogeneity	0.517	0.150	0.060	0.730
Households	664.409	304.001	108	1,796
% Old house	0.089	0.177	0	0.888
% Aged 65	0.120	0.082	0	0.431
% Aged 15–34	0.144	0.089	0.069	0.653

Descriptive statistics for the control variables are provided in Table 3. The concentrated disadvantage index has a mean of 0.224 (*SD*=0.111), indicating varying levels of economic hardship across CBGs. Residential instability averages 0.188 (*SD*=0.126), with a wide range from 0.012 to 0.499, suggesting significant differences in community turnover. Ethnic heterogeneity is moderate to high, with an average of 0.517 (*SD*=0.150). The average number of households per CBG is 664.4 (*SD*=304.0), reflecting neighborhood density variations.

Older homes, defined as those constructed before 1960, make up a small percentage overall (*M*=0.089, *SD*=0.177), although some areas report up to 88.8%, reflecting substantial variation in housing stock. Residents aged 65 or older constitute an average of 12.0% of the population (*SD*=0.082), while those aged 15 to 34 comprise 14.4% on average (*SD*=0.089). These demographic variables highlight the diversity of Arlington's CBGs and their potential relevance to burglary risk.

Regression Analysis

The relationship between the home capable guardian measure and burglary frequency was examined for specific time periods, including breakfast, lunch, dinner, night, work hours, after work hours, weekdays, and weekends. Tables 4 and 6 provide the results of the negative binomial regression models and Table 5 provides results of generalized spatial two stage least square model (GS2SLS).

Narrow Time Periods: Breakfast, Lunch, Dinner, and Nighttime. Table 4 focuses on the four specific time periods: breakfast (6:00–10:59 a.m.) (Model 1), lunch (11:00 a.m.–2:59 p.m.) (Model 2), dinner (5:00–8:59 p.m.) (Model 3), and nighttime (9:00 p.m.–midnight) (Model 4). During breakfast and lunch

Table 4. Negative Binominal Regression Models of Burglary per Block for Breakfast, Lunch, Dinner, and Night.

	Breakfast		Lunch		Dinner		Night time	
	Model 1		Model 2		Model 3		Model 4	
Model variables	IRRs	*SE*	IRRs	*SE*	IRRs	*SE*	IRRs	*SE*
Block group variables								
Home guardianship	1.232	1.238	1.023	1.133	0.040*	0.063	0.148**	0.656
Concentrated disadvantage	1.073	1.607	2.331	2.866	2.419*	2.857	1.056*	18.018
Residential instability	0.469	0.637	1.094	1.254	0.548	0.671	0.074	0.077
Ethnic heterogeneity	6.735	8.327	3.201	3.448	0.765	0.837	1.811	1.729
Number of households	1.002***	0.001	1.001***	0.001	1.001***	0.001	1.001***	0.001
% Old house	0.799	0.752	0.487	0.396	1.799	1.334	1.954	1.162
% Aged 65	28.925†	54.688	4.275	6.643	53.027*	89.918	1.475	2.178
% Aged 15–34	1.143	0.189	1.092	0.142	1.385*	0.202	1.387**	0.169
Spatially lagged variables								
Home guardian	0.687	1.671	4.757	11.849	30.661	98.591	2.441	2.543
Concentrated disadvantage	0.173	0.558	0.086	0.249	12.184	39.801	0.068	0.184
Residential instability	90.921†	243.360	149.532*	345.485	1.730	4.105	330.05**	710.86
Ethnic heterogeneity	0.201	0.457	0.401	0.812	0.363**	1,323.59	1.485	2.632
Households	0.999	0.001	0.999	0.001	0.999	0.001	0.998*	0.001
% Old house	0.257	0.411	2.404	3.269	0.259*	0.396	0.468	0.569
% Aged 65	0.001	0.006	0.001	0.005	1.025	0.056	0.031	0.105
% Aged 15–34	1.048	0.351	0.913	0.245	1.106	0.312	0.573*	0.158
Burglary	0.907	0.106	0.989	0.137	1.248*	0.301	1.076*	0.271
Intercept	0.281	0.534	0.314	1.526	0.001**	0.001	0.911	1.367

Note. N (block groups)225 = 166. IRR = incidence rate ratios; *SE* = standard error.
$^{*}p < .05$. $^{**}p < .01$. $^{***}p < .001$. † $p<0.1$.

Table 5. Generalized Spatial Two Stage Least Square Model (GS2SLS) of Burglary per Block for Breakfast and Lunch.

	Breakfast		Lunch	
	Model 5		Model 6	
Model variables	RRRs	*SE*	RRRs	*SE*
Block group variables				
Home guardianship	0.537	0.333	0.609	0.406
Concentrated disadvantage	1.414	1.507	1.030	0.913
Residential instability	3.835	3.155	2.683	1.913
Ethnic heterogeneity	1.102	0.717	1.302	0.753
Households	1.001***	0.001	1.000***	0.001
% Old house	0.913	0.458	0.751	0.330
% Aged 65	2.218	2.631	2.088	2.163
% Aged 15–34	1.008	0.099	1.015	0.087
Spatially lagged variables				
Home guardianship	2.465	1.105	2.347	1.246
Concentrated disadvantage	0.941	2.471	0.671	2.187
Residential instability	2.709	2.176	1.638	1.946
Ethnic heterogeneity	0.942	1.010	0.964	0.934
Households	0.001	0.001	0.001	0.001
% Old house	1.128	1.025	0.252	0.961
% Aged 65	1.467	1.908	1.592	1.795
% Aged 15–34	0.577*	0.291	0.001	0,266
Burglary	1.150	0.187	1.472	0.195
Spatial error variable				
Burglary	7.273***	0.208	5.164**	1.607
Intercept	0.419	0.437	0.331	0.406

Note. *N* (block groups) = 166. RRR = relative risk ratios; *SE* = standard error.
**p* < .05. ***p* < .01. ****p* < .001.

periods, home capable guardianship was not significantly associated with burglary frequency, suggesting no measurable protective effect during these intervals. However, significant effects were observed during dinner and nighttime periods. For dinner, a 96% reduction in burglary frequency was associated with an increase in home guardianship (Model 3, IRR = 0.040, $p < .05$). Similarly, during nighttime hours, a significant reduction of 85.2% in burglary risk was observed (Model 4, IRR = 0.148, $p < .01$).

Control variables revealed additional patterns. Concentrated disadvantage was positively associated with burglary risk during both dinner (Model 3,

Table 6. Negative Binominal Regression Models of Burglary per Block for Work-Hour, After Work-Hour, Weekdays and Weekends.

	Work-hour		After work-hour		Weekdays		Weekends	
	Model 7		Model 8		Model 9		Model 10	
Model variables	IRRs	*SE*	IRRs	*SE*	IRRs	*SE*	IRRs	*SE*
Block group variables								
Home guardianship	0.628	0.682	0.107**	0.939	0.4119	1.453	0.070*	0.094
Concentrated disadvantage	1.471	1.603	1.659*	1.413	1.116*	1.142	1.126	5.521
Residential instability	0.412	0.393	0.164	0.154	0.214	0.197	0.417	0.428
Ethnic heterogeneity	4.493	3.789	3.026	2.495	4.492	3.495	3.048	2.947
Number of households	1.001***	0.001	1.001***	0.001	1.001***	0.001	1.001***	0.001
% Old house	0.942	0.589	1.883	1.029	1.388	0.769	0.935	0.575
% Aged 65	6.924	9.114	2.465	3.296	4.168	5.295	8.987	12.090
% Aged 15–34	1.114	0.125	1.291*	0.142	1.215†	1.334	1.220†	0.137
Spatially lagged variables								
Home guardian	38.915	103.628	2.355	4.261	18.150†	30.074	3.253	6.342
Concentrated disadvantage	0.314	0.759	0.475	1.121	0.879	2.042	0.087	0.229
Residential instability	114.33*	234.677	26.355	49.731	66.312*	122.737	23.261	44.676
Ethnic heterogeneity	0.868	1.408	3.819	6.018	1.213	1.836	16.346	29.961
Households	0.999	0.001	0.998†	0.001	0.999	0.001	0.998	0.001
% Old house	0.409	0.465	0.300	0.337	0.254	0.275	1.738	2.052
% Aged 65	0.010	0.033	2.244	6.989	0.121	0.365	0.874	3.020
% Aged 15–34	1.109	0.258	0.734	0.172	1.010	0.235	0.894	0.227
Burglary	0.833	0.110	1.678*	0.373	0.930	0.076	1.343	0.280
Intercept	0.371	0.516	0.200	0.274	0.301	0.393	0.073	0.113

Note. N (block groups) = 166. IRR = incidence rate ratios; *SE* = standard error.
$^{*}p < .05$. $^{**}p < .01$. $^{***}p < .001$. † $p<0.1$.

IRR = 22.419, $p < .05$) and nighttime (Model 4, IRR = 16.056, $p < .05$), highlighting the vulnerability of socioeconomically disadvantaged areas during these times. The proportion of younger residents (aged 15–34) was also positively correlated with burglary, with a 38.5% increase during dinner (Model 3, IRR = 1.385, $p < .05$) and a 38.7% increase at night (Model 4, IRR = 1.387, $p < .01$).

Spatial effects were notable as well. Greater ethnic heterogeneity in neighboring block groups significantly reduced burglary risk during dinner (IRR = 0.363, $p < .01$), potentially reflecting the protective effects of social cohesion. Conversely, residential instability in neighboring areas increased burglary risk at night, possibly due to weakened social controls. Additionally, a clustering effect was observed, with recent burglaries in neighboring areas significantly elevating local burglary risk during both dinner (IRR = 1.248, $p < .05$) and nighttime (IRR = 1.076, $p < .05$).

Given the lack of significant associations between home guardianship and burglary during the breakfast and lunch periods in the negative binomial regression models, further analysis with Generalized Spatial Two-Stage Least Squares (GS2SLS) was conducted using Stata 18. This approach allows for the inclusion of spatial lags for both dependent and independent variables, as well as spatial autoregressive error terms, providing a robust method for addressing spatial dependence and unmeasured contextual factors (Elhorst, 2014).

Table 5 presents the results of GS2SLS models (Models 5 and 6) for breakfast (6:00–10:59 a.m.) and lunch (11:00 a.m.–2:59 p.m.) periods. The home guardianship measure remained non-significant in both models, reaffirming the earlier findings that guardianship had no measurable effect on burglary during these time periods. However, the spatial error terms were significant in both models ($p < .05$), indicating the presence of spatial dependence driven by unmeasured factors. This suggests that burglary risks during breakfast and lunch are influenced by broader spatial processes that extend beyond the focal block group.

In terms of control variables, concentrated disadvantage and residential instability exhibited inconsistent effects across these periods, with neither consistently reaching statistical significance. The absence of significant relationships may reflect the reduced influence of social disorganization factors during daytime hours, when residents are less likely to be at home and social controls are less active.

The significant spatial error terms highlight the importance of accounting for spatial dependence in understanding burglary dynamics. These findings suggest that traditional regression approaches may underestimate or misattribute the influence of local guardianship and contextual factors without accounting for spatially autocorrelated processes.

Broader Time Periods: Work Hours, After Hours, Weekdays, and Weekends. Table 6 extends the analysis to broader intervals: work hours (Monday to Friday), after work hours (Monday to Friday), weekdays, and weekends. During work hours (Model 7), home guardianship was negatively associated with burglary, but the effect was not statistically significant. The number of households within a block group was positively associated with burglary risk (IRR = 1.001, $p < .001$), indicating that higher numbers of potential targets may slightly increase risk. Spatially, residential instability in neighboring areas significantly elevated burglary risk in the focal block (IRR = 114.33, $p < .05$).

In contrast, home guardianship during after work hours (Model 8) significantly reduced burglary frequency by 89.3% (IRR = 0.107, $p < .01$). Concentrated disadvantage (IRR = 1.659, $p < .05$) and a higher proportion of younger residents (IRR = 1.291, $p < .05$) were associated with increased burglary risk during this period. Spatially, recent burglaries in neighboring areas also elevated burglary risk (IRR = 1.678, $p < .05$).

On weekdays (Model 9), home guardianship was not significantly associated with burglary. However, concentrated disadvantage (IRR = 1.116, $p < .05$) and residential instability in neighboring areas (IRR = 66.312, $p < .05$) were positively associated with burglary risk. On weekends (Model 10), home guardianship significantly reduced burglary frequency by 93% (IRR = 0.070, $p < .05$), underscoring the protective role of resident presence. The number of households in the block group was also positively associated with burglary risk (IRR = 1.001, $p < .001$).

In summary, home capable guardianship significantly reduces burglary risk during dinner, nighttime, after work hours, and weekends. However, its effects are less evident during weekday work hours, breakfast, and lunch periods.

Discussion

The findings of this study provide new insights into the role of capable guardianship in deterring residential burglary, expanding the theoretical framework of routine activity theory (RAT) by leveraging mobile phone tracking data. These results confirm and extend existing criminological research (Felson, 2017; Hipp & Williams, 2020; Reynald, 2011) in several key ways. Specifically, they highlight the utility of temporally granular measures of human mobility for understanding capable guardianship and its effects on residential burglary risks.

The comparative analysis of burglary distribution maps highlights notable spatial and temporal differences. As shown in Figures 2 and 3, burglary incidents are concentrated in Arlington's South and North divisions, with a particularly high density in the northern areas during nighttime hours. The South division predominantly houses African-American residents in multi-family rental units, while the North division features a racially and ethnically diverse population, a mix of housing types, and higher levels of non-residential land use, such as industrial and entertainment zones. Patterns differ between weekdays and weekends, with weekday burglaries concentrated in the northern and northeastern areas and weekend burglaries more prevalent in the east-south regions. These variations suggest that targeted interventions focusing on specific times and locations could enhance crime prevention efforts, particularly in areas with heightened vulnerability.

The analysis of home capable guardian proportions (Figures 4 and 5) further illustrates important spatial dynamics. Higher proportions of home guardians are observed on the city's outskirts, where single-family homes and apartments are more common. Conversely, the central areas exhibit lower proportions of guardianship due to higher concentrations of retail, entertainment, and industrial land uses. The proportion of home guardianship increases throughout the day, especially in southern and western areas, reflecting residents returning home after work. However, this progression is slower in the South and East, where minority residents often work non-standard schedules. This suggests a need for targeted interventions to enhance guardianship in areas where residents may be less available during key periods.

The descriptive analysis of human mobility patterns reveals expected trends. Across the studied census block groups (CBGs), the proportion of individuals staying at home is highest during nighttime, after work hours, and on weekends. These findings validate the use of mobile phone data as a reliable proxy for measuring human presence within residential settings. Furthermore, the descriptive results align with previous research (e.g., Felson, 1987; Groff & La Vigne, 2002) demonstrating that burglary rates tend to be higher during weekday mornings and afternoons—particularly breakfast and lunch periods—when residents are typically away from home and less able to act as capable guardians.

The regression models provide additional evidence supporting the protective role of home guardianship during specific time periods. Significant reductions in burglary frequency were observed during dinner, nighttime, and after work hours, where the proportion of home devices was associated with decreases in burglary ranging from 24% to 27%. These findings align with what we know about the situational effectiveness of guardianship (Reynald, 2011) and emphasize the broader criminological understanding that informal guardianship—such as residents being home—serves as a critical deterrent to crime (Felson, 2006). Importantly, this study extends prior research by incorporating temporally precise data on human presence, offering a level of granularity rarely achieved in earlier studies.

Conversely, the lack of significant associations between home guardianship and burglary during breakfast, lunch, weekday, and weekend periods suggests that the effectiveness of guardianship may vary depending on the availability of other contextual factors. The significant spatial error terms in the GS2SLS models for breakfast and lunch highlight the role of unmeasured, spatially autocorrelated factors. These factors may include alternative forms of guardianship, such as the presence of visitors or passersby, which could mitigate burglary risks during these periods. This finding underscores the importance of understanding the situational effectiveness of guardianship, as posited by the situational crime prevention framework (Clarke, 1995). Nighttime informal guardianship, by contrast, may be particularly effective as other forms of guardianship—such as visitors and passersby—are less likely to be present, and police patrols may be less frequent.

A particularly noteworthy finding is the absence of spatial spillover effects for home guardianship across adjacent neighborhoods. Unlike social disorganization factors, the presence of residents in their homes had no significant impact on burglary rates in neighboring CBGs. This aligns with RAT, which posits that capable guardianship operates locally, within the immediate vicinity where motivated offenders and suitable targets converge. These results emphasize the need for place-specific crime prevention strategies.

These findings have significant implications for crime prevention strategies and policies. Understanding the temporal and spatial dynamics of resident presence can help policymakers and law enforcement agencies develop targeted interventions to enhance capable guardianship during vulnerable times. For example, increasing police patrols or community watch activities during breakfast and lunch periods could help mitigate burglary risks in areas where residents are typically away from home during the conventional work hours. By identifying specific "at-risk hours" when residents are absent from home, law enforcement could schedule increased police patrols or community watch activities. This could also include having neighborhood patrols increase in areas that experience a higher concentration of vacancies or absentee residents. For example, in case of Arlington, one might suggest that enhanced patrolling areas on the north and south during the breakfast times might produce noticeable crime reduction effect for residential burglaries. Importantly, efforts to increase patrols or surveillance in minority neighborhoods should be carefully considered to avoid over-policing and its associated negative consequences.

Technological solutions could also play a pivotal role in supplementing human guardianship. Automated lighting systems that simulate human presence, motion-sensor-equipped cameras, and smart home security devices such as video doorbells and smart locks could be strategically deployed in high-risk areas and used during "at-risk hours" identified through crime trend analyses. Specifically to Arlington, TX, it appears that areas with low residential presence but high frequency of robberies (e.g., East Arlington) would benefit from such technological solutions mitigating the absence of capable human guardianship. Given the role of concentrated disadvantage in residential burglaries, landlords, and property owners of multifamily units should be encouraged to share the cost of safety devices, making them more accessible to low-income tenants. Furthermore, integrating community-based approaches, such as neighborhood watch programs and social cohesion initiatives, could enhance informal guardianship and reduce reliance on formal law enforcement in vulnerable areas.

The success of hotspot policing strategies (e.g., Braga et al., 2014), underscores the importance of focused, data-driven interventions. By leveraging this study's findings on spatial and temporal dynamics of burglaries, law enforcement, urban planners, and community residents can allocate resources more effectively.

In conclusion, this study contributes to the criminological literature by providing temporally and spatially granular insights into the role of capable guardianship in preventing residential burglary. The use of mobile phone data offers a novel and more precise method for measuring resident presence, addressing limitations in prior research that relied on static or aggregate data sources. The findings underscore the importance of localized and targeted crime prevention strategies that account for the temporal dynamics of human mobility and neighborhood-specific vulnerabilities. Future research should explore the potential for integrating additional forms of guardianship, such as formal policing and technological solutions, to further enhance residential security and reduce burglary risks.

Limitations

This study's findings must be interpreted in light of several limitations. A primary constraint stems from the secondary nature of the data provided by Advan, a for-profit research entity specializing in foot traffic analytics primarily for marketing purposes. Advan's data collection methodology prioritizes areas with significant commercial activity, excluding census block groups (CBGs) with minimal or no "points of interest" (POIs). Specifically, only CBGs containing at least 1,000 POIs are included in the datasets available through the Dewey subscription service. As a result, this study's analysis was confined to 166 out of the 252 CBGs in Arlington, Texas. While this exclusion could potentially affect the generalizability of the findings, Table 1 indicates only minor differences between included and excluded CBGs in demographic variables such as racial composition, and other key factors like social disorganization and residential land use appear comparable. Additionally, Figure 1 demonstrates no spatial clustering of missing CBGs, reducing concerns about systematic bias in the dataset.

Another limitation arises from the assumption that all cell phone devices detected within a home area represent individuals who remain at their residences. This assumption could be violated for individuals who work within the same CBG as their residence. However, given that the average urban CBG spans less than one mile and only 8.7% of Arlington commuters in 2019 drove less than 10 min to work (U.S. Census Bureau, 2019), the proportion of individuals affected by this limitation is likely small. Therefore, the study's measure of capable guardianship is unlikely to be significantly impacted by this potential confound.

Although cell phone mobility data is widely regarded as a robust proxy for human mobility dynamics (Palmer et al., 2013), it is not without limitations. As of 2023, approximately 98% of Americans possessed at least one mobile device, but ownership rates are lower among specific demographic groups, including individuals aged 65 and older and those in households earning less than $30,000 annually (Vogels, 2021). A recent analysis of cell phone mobility data over a 5-year period found strong correlations between sampled devices and census population estimates at the county level but weaker correlations at the CBG level (Li et al., 2024). Sampling biases were more pronounced for rural areas, low-income populations, and African-American individuals, though these biases showed a declining trend between 2018 and 2021. While the remaining sampling gaps, particularly for African-American individuals, may introduce some bias in the measurement of capable guardianship, the widespread adoption of mobile devices minimizes the likelihood of significant exclusions. Moreover, alternative measures of ambient population, such as social media data, are associated with even greater exclusions for underrepresented groups, underscoring the relative inclusivity of cell phone-based metrics.

The dependent variable in this study encompasses all residential burglary incidents classified under the Uniform Crime Reporting (UCR) category of "burglary of habitation." In Texas, this includes crimes involving the "entering or remaining concealed in a habitation not open to the public, with intent to commit a felony, theft, or assault" (Texas Penal Code, Sections 30.02(c)(2) and 30.02(d)). This broad categorization inherently includes burglary types, such as deceit-based offenses, where the presence of residents may not serve as a deterrent but rather be a necessary condition for the crime. Unfortunately, this dataset lacks the granularity needed to isolate deceit-based burglaries. However, given that the majority of residential burglaries in 2019 involve the use or attempted use of force, the findings are applicable to a large number of burglary incidents.[3]

Another notable limitation of this study is its reliance on human mobility and residents' presence at home as the sole indicators of capable guardianship. This narrow operationalization overlooks other critical dimensions of guardianship that may influence burglary risk. For instance, technological interventions such as alarm systems, smart locks, and surveillance cameras are increasingly relevant in modern guardianship dynamics. Future research should incorporate these additional factors to provide a more comprehensive understanding of how various elements of guardianship interact and collectively influence residential burglary. Such an approach could offer nuanced insights into how human presence and security measures complement each other in crime deterrence. Furthermore, the built environment's characteristics are likely to influence burglary patterns, yet these factors were not explicitly accounted for in this study. While the census block group (CBG) serves as a meaningful unit of analysis, it may not consistently capture the built environment's nuances, particularly in areas with mixed land use. Future studies should consider incorporating detailed environmental attributes, such as street lighting, visibility obstructions, and proximity to high-traffic areas, to better understand environmental deterrents to crime. Additionally, proxy measures for law enforcement presence, such as patrol frequency or community policing activities, could enrich the analysis by highlighting the broader protective landscape within neighborhoods.

The study's reliance on CBGs also presents limitations in areas where built environments are heterogeneous within a single block group. For example, mixed-use developments that combine residential, commercial, and industrial spaces may exhibit different patterns of guardianship and burglary risk that cannot be fully captured at the CBG level. Incorporating finer-grained spatial units or advanced geospatial modeling techniques could address this issue and offer more precise insights into the interaction between land use and burglary risk.

Finally, the mobility patterns of offenders remain an important yet unexplored dimension of this research. While the routine activities of offenders likely contribute to the observed patterns, this study could not directly analyze offender mobility due to data limitations. Emerging technologies, such as wearable electronic devices, AI-driven surveillance footage analysis, and crowdsourced tracking through third-party platforms, could enable future research to incorporate offender behavior. Although these approaches face challenges related to reliability, privacy concerns, and generalizability, they hold potential for advancing the understanding of how spatial and temporal offender dynamics intersect with capable guardianship to influence residential burglary.

Future Research Recommendations

This study's limitations highlight several areas for future research that can enhance the understanding of capable guardianship and its role in deterring residential burglary. Addressing these gaps offers opportunities to advance theoretical, methodological, and practical contributions within the RAT framework.

Future studies should prioritize expanding data coverage beyond areas with substantial commercial activity. Collaborating with data providers to include residential zones with fewer "points of interest" (POIs) would improve the representativeness and generalizability of findings. Integrating alternative data sources, such as traffic flow patterns, smart city infrastructure, and social media geotags, could also enrich mobility metrics in underserved areas.

While this study focused on resident presence as a measure of capable guardianship, future research should explore other dimensions of guardianship, including technological and formal mechanisms. Security devices such as alarm systems, smart locks, and video surveillance should be evaluated to assess how they complement or substitute for human presence. Additionally, examining the interactions between informal guardianship and formal law enforcement activities, such as patrol frequency and response times, can provide a more comprehensive understanding of crime prevention.

Incorporating built environment characteristics into analyses may also yield deeper insights. Variables such as street lighting, visibility obstructions, and proximity to high-traffic areas could be examined to understand their role in deterring or facilitating residential burglary. Future studies could use advanced geospatial methods to analyze these factors at finer spatial resolutions, which may better capture the heterogeneity of land use within census block groups.

Another critical avenue for research is the mobility patterns of offenders. Exploring how offender routines intersect with capable guardianship and environmental characteristics could refine the understanding of burglary risks. Emerging technologies, such as AI-driven surveillance analysis and wearable tracking devices, could provide valuable data for these investigations, though ethical considerations regarding privacy will need to be addressed.

Equity in access to guardianship measures also warrants further study. Low-income and minority populations may face barriers to adopting security technologies. Research should explore strategies for landlords and property owners to subsidize the costs of these devices, potentially enhancing guardianship in socioeconomically disadvantaged areas. Evaluating the effectiveness of these interventions could inform equitable policies for crime prevention.

Finally, longitudinal and comparative analyses offer valuable opportunities for future research. Examining changes in guardianship effectiveness over time, in response to urban development, demographic shifts, or technological advancements, could provide dynamic insights. Comparative studies across cities with diverse socioeconomic and geographic contexts may also identify factors that influence the relationship between guardianship and residential burglary.

By addressing these areas, future research can build upon the findings of this study, contributing to a more nuanced understanding of capable guardianship. These efforts will not only advance the theoretical framework of RAT but also inform the development of targeted, data-driven strategies for reducing residential burglary.

This study provides valuable insights into the role of capable guardianship within the framework of routine activity theory, offering partial support for its construct by demonstrating that the proportion of residents who stay home has a direct negative association with burglary frequency during specific time periods. Unlike prior studies that relied on indirect measures of guardianship—such as the use of protective devices or the presence of law enforcement—this study proposed and empirically tested a frequently discussed but previously unmeasurable dimension of capable guardianship: the physical presence of residents in their homes. By leveraging mobile phone data, this study highlights a novel and promising methodological approach for examining core criminological concepts with greater precision.

The findings reveal that the use of cell phone mobility data offers a replicable and scalable method for measuring capable guardianship, with potential applications across diverse geographic settings. The data provided by Advan, collected uniformly across the United States, allow for the proposed measure to be easily adapted by researchers in different urban, suburban, or rural contexts. This adaptability is a notable strength, as it enables comparisons across regions with varying demographic, socioeconomic, and spatial characteristics. Moreover, the study's methodological approach facilitates temporally granular analyses, uncovering insights into the situational and localized effectiveness of capable guardianship.

By advancing a novel measurement approach and providing detailed temporal and spatial analyses of capable guardianship, this study contributes to both criminological theory and practice. It underscores the importance of localized, data-driven crime prevention strategies that account for the dynamics of human mobility and neighborhood-specific vulnerabilities. The findings affirm the value of integrating emerging technologies into criminological research to enhance the understanding and practical application of key theoretical constructs, ultimately contributing to more effective resource allocation and community safety initiatives.

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Notes

1. This data was made available by Advan Research (https://advanresearch.com) via the subscription to Dewey Data platform (https://www.deweydata.io)
2. See more on differences of methodology between Advan and SafeGraph at https://www.deweydata.io/blog/advan-patterns-now-available
3. See for example https://ucr.fbi.gov/crime-in-the-u.s/2019/crime-in-the-u.s.-2019/topic-pages/burglary

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