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Understanding Temporal and Distance-Based Human Mobility Patterns Using Foot Traffic Data

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Abstract

Population movement across time and space plays a critical role in transportation planning, urban accessibility, and public health analysis. In this study, an anchoring-based mobility modeling framework was developed to characterize temporal and distance-based population-level human mobility patterns using massive aggregated mobility data. Specifically, the framework develops a novel continuous Anchoring Index which quantifies the relative spatial dependence of activity categories on residential (home) versus daytime (work-related) anchors using visit-weighted distance measures. The framework illustrates temporal heterogeneity in mobility behavior by separating activity patterns across weekdays and weekends and across peak and off-peak periods. Distance-based mobility behavior is examined through an OLS regression model capturing category-level and regional determinants of distance from home, while a Multinomial Logit model independently characterizes the temporal determinants of activity category choice across 18 functional destination types without incorporating distance as a predictor. Building on these distance-based metrics, the study portrays mobility flows as category-region networks, which allows structural analysis of connectivity, centrality, and spatial coupling between activities and locations. Instead of focusing on individual-level choice models, the introduced methodology prioritizes interpretability and scalability, making it ideal for population-level analysis. The empirical findings indicate stark differences in anchoring behavior between activity types, including the strong residential anchoring evident for essential services, flexible spatial patterns characteristic of discretionary activities, and pronounced daytime anchoring seen for work-related categories. The results show that both anchoring-based and network-based representations jointly yield a strong yet interpretable framework to understand large human mobility systems as well as their evolution in time, with relevance for accessibility analysis, transport policy, or urban system resilience.

Keywords

Human Mobility Patterns, Anchoring Index, Distance-Based Mobility Analysis, Temporal Mobility Dynamics, Activity Category Analysis, Population-Level Mobility, Mobility Network

1. Introduction

Human mobility plays a central role in shaping access to employment, healthcare, education, and essential services, thereby influencing social equity, economic opportunity, and overall quality of life in urban and regional systems. Everyday movement patterns reflect how individuals and communities interact with the built environment and respond to transportation availability, land-use configurations, and activity demands. As a result, understanding mobility behavior has become a fundamental concern in transportation planning, urban studies, and accessibility research. Prior studies have shown that disparities in mobility are closely linked to unequal access to opportunities and services, making mobility analysis critical for evidence-based policy and infrastructure planning [1]-[3].

Recent advances in large-scale mobility data have created new opportunities to examine human movement at the population level with greater spatial and temporal resolution than previously possible. The increasing availability of aggregated mobility datasets, including mobile phone data, location based services, and foot traffic records, allows researchers to move beyond traditional travel surveys and traffic counts, which are often limited in sample size, frequency, and spatial coverage [4] [5]. Population-level mobility data capture collective movement behavior over extended periods, enabling the identification of recurring patterns, dominant activity rhythms, and systemic constraints while preserving individual privacy. These data-driven approaches have become increasingly important for understanding how mobility systems function in practice rather than how they are assumed to operate in planning models [6] [7].

Despite these advances, much of the existing research on human mobility remains constrained by data sources and analytical perspectives that capture only partial aspects of everyday movement behavior. Vehicle traffic counts and roadway sensors primarily reflect motorized travel and overlook pedestrian activity and short-distance trips that constitute a substantial portion of daily mobility, particularly in dense urban environments [8]. Similarly, travel surveys, while rich in behavioral detail, are limited by small sample sizes, infrequent collection cycles, and potential reporting bias, reducing their ability to capture fine-grained temporal variability and long-term population-level trends [4]. Transit based datasets further exclude walking-only and informal travel, resulting in an incomplete representation of mobility systems. Consequently, existing approaches often fail to fully characterize how people move in their daily lives, particularly outside of vehicle-oriented and peak-period travel contexts [9].

Beyond data limitations, a key conceptual gap in the mobility literature lies in the tendency to analyze temporal and distance-based dimensions of movement independently.

Numerous studies have examined temporal mobility patterns, such as daily and weekly activity cycles, peak-period demand, and routine regularity, to understand travel behavior and system performance [10] [11]. In parallel, distance-based and spatial interaction studies have focused on trip length distributions, distance decay effects, and accessibility measures to evaluate spatial opportunity and land-use efficiency [12] [13]. However, relatively few studies jointly consider when people move and how far they travel within a unified analytical framework. Treating these dimensions in isolation limits the ability to identify mobility constraints, uncover accessibility challenges, and interpret population-level movement behavior in a comprehensive manner.

To address these limitations, this study adopts a population-level perspective to examine human mobility through the joint analysis of temporal and distance-based movement patterns. By focusing on aggregated mobility behavior rather than individual trajectories, population-level analysis enables the identification of recurring rhythms, dominant travel distances, and structural constraints that emerge from the interaction between transportation systems, land use patterns, and daily activity demands [6] [7]. Integrating temporal and distance dimensions provides a more comprehensive understanding of when people move and how far they travel, offering insights into accessibility conditions and mobility constraints that are not observable when these dimensions are analyzed separately. Using long-term foot traffic data spanning multiple years, this study develops an integrated analytical framework to characterize population-level mobility patterns and their variability across time and space. The findings contribute to the growing body of mobility research by demonstrating how combined temporal-distance analysis can inform transportation planning and accessibility assessment, while supporting data-driven decision-making reflects everyday movement behavior.

The remainder of this paper is organized as follows. Section 2 reviews relevant literature on temporal mobility dynamics, distance-based movement behavior, and population-level mobility analysis using aggregated data. Section 3 describes the foot traffic dataset, including its spatial and temporal coverage, key variables, and preprocessing procedures. Section 4 presents the methodological framework used to analyze temporal and distance-based mobility patterns at the population level. Section 5 discusses the results, highlighting key temporal rhythms, distance characteristics, and activity-dependent mobility patterns. Section 6 provides a discussion of the findings, including implications for population-level mobility analysis and accessibility assessment, as well as study limitations. Finally, Section 7 concludes the paper and outlines directions for future research.

2. Related Works

This section reviews existing studies related to human mobility analysis, with a particular focus on temporal mobility dynamics, distance-based movement behavior, and population-level mobility analysis using aggregated data. The review synthesizes prior research that has examined when people move, how far they travel, and how large-scale mobility datasets have been used to characterize collective movement patterns. In addition, this section highlights key methodological and conceptual limitations in the existing literature, particularly the limited integration of temporal and distance dimensions in mobility analysis. The following subsections provide a structured discussion of these research streams to establish the context and motivation for the proposed population-level temporal-distance framework.

2.1. Human Mobility and Temporal Dynamics

Temporal dynamics have long been recognized as a fundamental dimension of human mobility, reflecting how daily activities, social obligations, and transportation systems shape when people move. Early mobility research emphasized the role of time in structuring travel behavior, demonstrating that human movement follows regular daily and weekly rhythms driven by work schedules, school hours, and service availability [10] [14]. These temporal regularities have been widely used to identify peak travel periods, assess system performance, and inform transportation planning and demand management strategies.

Subsequent studies have leveraged increasingly detailed mobility data to examine temporal variability in travel behavior, including differences between weekdays and weekends, seasonal fluctuations, and deviations from routine patterns. Research using travel diaries and time-use surveys has shown that temporal constraints strongly influence trip timing, duration, and frequency, often limiting individuals' ability to adjust their schedules in response to congestion or service disruptions [4] [15]. More recent work utilizing large scale mobility datasets, such as mobile phone records and location-based services, has further revealed stable temporal signatures of human activity across cities, highlighting the predictability of collective movement patterns over time [5] [11].

Temporal mobility patterns have also been linked to broader questions of accessibility and equity. Studies have shown that irregular or highly constrained temporal movement may indicate limited transportation options, inflexible work conditions, or restricted access to essential services, particularly for disadvantaged populations [16] [17]. Peak-period congestion and off-peak service gaps can create temporal barriers that disproportionately affect individuals with limited schedule flexibility, reinforcing existing inequalities in access to opportunities.

Despite these advances, much of the temporal mobility literature focuses primarily on when movement occurs, with limited consideration of the spatial extent or distance associated with observed temporal patterns. Temporal analyses are often conducted independently of trip length or spatial reach, making it difficult to assess whether observed activity rhythms correspond to short, localized movements or longer-distance travel driven by service scarcity or spatial mismatch. As a result, while temporal dynamics provide valuable insight into the timing and regularity of mobility behavior, they offer an incomplete understanding of everyday movement when examined in isolation from distance-based considerations.

2.2. Distance-Based Mobility Behavior

Distance-based mobility analysis has been widely used to examine the spatial extent of human movement and to assess how access to opportunities is shaped by the built environment and transportation systems. Early studies in transportation and urban economics emphasized trip length distributions and distance decay effects as fundamental characteristics of travel behavior, demonstrating that the likelihood of interaction between locations generally decreases with increasing distance [12] [18]. These approaches have been central to understanding spatial interaction, land-use efficiency, and the organization of urban activity systems.

Subsequent research has expanded distance-based analysis to explore accessibility, spatial mismatch, and service availability. Trip distance has frequently been used as a proxy for spatial opportunity, with shorter trips often interpreted as indicators of compact urban form or constrained mobility, and longer trips associated with service scarcity, employment dispersion, or inefficiencies in land-use planning [9] [19]. Accessibility-based studies have further linked travel distance to socioeconomic outcomes, highlighting how longer travel requirements can impose disproportionate burdens on certain populations [16] [20].

With the emergence of large-scale mobility datasets, recent studies have examined distance-based movement patterns at unprecedented spatial resolution. Analyses using mobile phone data, GPS traces, and location-based services have revealed consistent distributions of travel distances across cities, as well as scaling relationships between trip length, urban size, and activity type [5] [21]. These findings suggest that distance-based mobility behavior exhibits stable statistical properties at the population level, making it a valuable lens for comparative urban analysis and system-level evaluation.

Despite these contributions, distance-based mobility studies frequently abstract movement from its temporal context. Trip length and spatial reach are often analyzed independently of the timing, frequency, or regularity of travel, limiting the ability to distinguish between short-distance routine activities and longer-distance trips constrained to specific time windows. As a result, distance-based analyses alone provide limited insight into how spatial accessibility interacts with temporal constraints to shape everyday mobility behavior. This separation restricts a comprehensive understanding of population-level movement patterns, underscoring the need for integrated temporal-distance approaches.

2.3. Population-Level Mobility Analysis Using Aggregated Data

Population-level mobility analysis has gained increasing attention as researchers seek to understand collective movement behavior while avoiding the limitations and privacy concerns associated with individual-level tracking. Rather than focusing on personal travel decisions, population-level approaches examine aggregated mobility patterns to reveal recurring rhythms, dominant travel behaviors, and systemwide dynamics that emerge from the interaction of individuals with transportation networks and urban form [6]. This perspective aligns closely with transportation planning and policy analysis, which prioritize demand patterns, peak loads, and accessibility conditions at the system level.

Early population-level studies relied on aggregated traffic counts and census-based travel indicators to infer spatial and temporal patterns of movement. While informative, these data sources were often limited in their ability to capture non-motorized travel, short-distance trips, and fine-grained temporal variability [4]. More recent advances in data availability have enabled population-level mobility analysis using large-scale digital traces, including mobile phone records, location-based services, and foot traffic datasets. These sources provide continuous observations across extended periods, allowing researchers to identify stable mobility signatures, compare activity patterns across locations, and assess changes in movement behavior over time [5] [7].

Aggregated mobility data have been widely applied to study urban activity patterns, land-use interactions, and accessibility dynamics. Studies have shown that population level movement exhibits regular statistical properties, such as predictable temporal cycles and consistent distance distributions, despite individual-level variability [11] [21]. By focusing on collective behavior, population-level analysis can uncover structural constraints such as limited-service availability or transportation capacity that are not easily detectable through individual travel records alone [9] [16].

2.4. Network Analysis for Mobility Patterns

Network analysis is a potent tool to explain mobility, as it treats locations as nodes of a network and movements between them as weighted edges that can be quantified within the framework of complex systems [22]. The connectivity of mobility networks, the extent to which areas are connected through the movement of humanity, shines brightly as an important determining factor of local and regional dynamics [23]. Centrality measures identify the position of a location within networks and highlight those hubs that are at the center of human flows [24], where people tend to aggregate and disperse in a highly evident, unequal manner. Temporal networks, *i.e.*, networks based on human mobility, show that the topology of movement between places is highly heterogeneous across time of day, seasons, and other external perturbations, undermining fixed, static network models [25]. The two-dimensional spatio-temporal approach that brings together temporal and distance-based dimensions into network frameworks shows how physical accessibility and temporal regularities together govern human movement patterns [26].

Spatial coupling, that is, the extent to which spatial proximity and structural network properties interact to produce mobility outcomes, represents an emergent outcome, one that cannot be understood from either spatial terms or the characteristics of the interrelations represented in networks alone [24]. Latest studies of mobility networks in various contexts show that connectivity and centrality are not isolated properties but rather closely linked with a spatial dimension of urban areas, the accessibility to infrastructure or land use organization, as well as socioeconomic tendencies at places [27]. Human mobility networks are inherently multilayer and temporal in nature, making it necessary for centrality measures to consider the structural roles of locations within static network topologies as well as their dynamic importance across different temporal scales [28]. The spatial coupling dynamics arise most clearly in the context of storms and other disruptive events: mobility networks reorganize structurally over extremely short time scales, as long-distance connections are increasingly broken while local clustering increases to a greater or lesser extent, with fundamental implications for how we characterize connectivity and centrality metrics [29]. Hence, to sensitively model large-scale phenomena like epidemic spreading through meta-population networks, it is essential to recognize these three interwoven facets of mobility: connectivity, centrality, and spatial coupling [30].

Despite these methodological advances, relatively few studies have leveraged aggregated mobility data to jointly examine temporal and distance-based dimensions of movement within a unified analytical framework. Existing population-level analyses often emphasize either temporal regularity or spatial extent independently, rather than exploring how the interaction of when and how far people travel reflects accessibility conditions and mobility constraints. As a result, the potential of population-level data to provide an integrated understanding of everyday mobility behavior remains underutilized. Addressing this gap requires analytical approaches that simultaneously capture temporal dynamics and distance-based patterns to reveal the structural characteristics of population-level movement systems.

3. Methodology

To explore differences in population-level mobility behavior across space and time, I adopted a descriptive, interpretable modeling framework based on concepts of spatial anchoring and temporal aggregation rather than predictive choice models. This methodology creates aggregate mobility indicators and normalized distance-based metrics, which represent how the activities are located around residential and daytime anchors. Temporal structures are clearly embedded by day of week (e.g., weekdays versus weekends) and by time of day (e.g., peak versus off-peak periods), facilitating systematic evaluations for temporal regularities in mobility behavior. I assessed distance-based metrics across activity categories and regions, with further interpretation of results using networks that define the structure and strength of connections between regions and types of activities. This modeling approach aims to reveal behavioral patterns and spatial organization in human mobility without imposing causal assumptions a priori, thereby favoring interpretability and population-level inference.

3.1. Data Collection and Description

The study utilizes the Weekly Patterns+ foot traffic dataset from Dewey, a SafeGraph-derived mobility dataset that offers aggregated and anonymized insights into human mobility patterns. It tracks activities from Monday to the end of Sunday in each period. Available from January 1st, 2018, to June 30th, 2025, the dataset covers 50 states across the United States and reports mobility at the Census Block Group (CBG) and point of interest (POI) levels. These 50 states include: Alaska, Arizona, Arkansas, Alabama, Washington, Oregon, Montana, Idaho, Nevada, California, New Mexico, Texas, Florida, Mississippi, Oklahoma, Utah, Colorado, Wyoming, Nebraska, South Dakota, North Dakota, Kansas, Louisiana, Georgia, Massachusetts, North Carolina, Delaware, Maryland, Rhoda Island, Virginia, Ohio, Iowa, Minnesota, Indiana, Tennessee, Kentucky, West Virginia, New York, New Jersey, South Carolina, Maine, New Hampshire, Wisconsin, Michigan, Illinois, Vermont, Pennsylvania, Connecticut, Hawaii, Missouri.

The data was derived from mobile device location pings collected through opt-in applications. Each observation level represents the aggregated weekly total visits and stops at the point of interest (POI) levels to preserve user privacy. In addition, the analytical sample was constructed by including POI-week observations with full weekly visitation information, valid temporal activity distributions, and non-missing distance-based mobility measures. Records were excluded from the analysis if they had incomplete geographical identifiers, an incomplete distribution for hourly visitation, duplicate observations, or no activity at all in the location. This structure enables the analysis of temporal and distance-based human mobility patterns across diverse geographic states in the United States.

- 2018: ≈2 million records
- 2019: ≈2 million records
- 2020: ≈2 million records
- 2021: ≈2 million records
- 2022: ≈2 million records
- 2023: ≈2 million records
- 2024: ≈2 million records
- 2025: ≈1 million records

Each dataset includes essential foot traffic attributes such as visit counts, stop frequency, temporal activity distributions by hour and day, stops by day, dwell-time indicators, device type information, and spatial identifiers.

The analytical framework adopted in this study follows a structured four-stage workflow illustrated in **Figure 1**. Beginning with data collection and preprocessing, the framework progresses through feature engineering, modelling and analysis, and evaluation and interpretation. The modelling and analysis stage encompasses four complementary components: spatiotemporal analysis, network analysis, distance modelling via OLS regression, and behavioural modelling via the Multinomial Logit model. Each stage builds sequentially on the outputs of the preceding stage, ensuring analytical consistency across temporal, spatial, and behavioral dimensions of population-level mobility behavior.

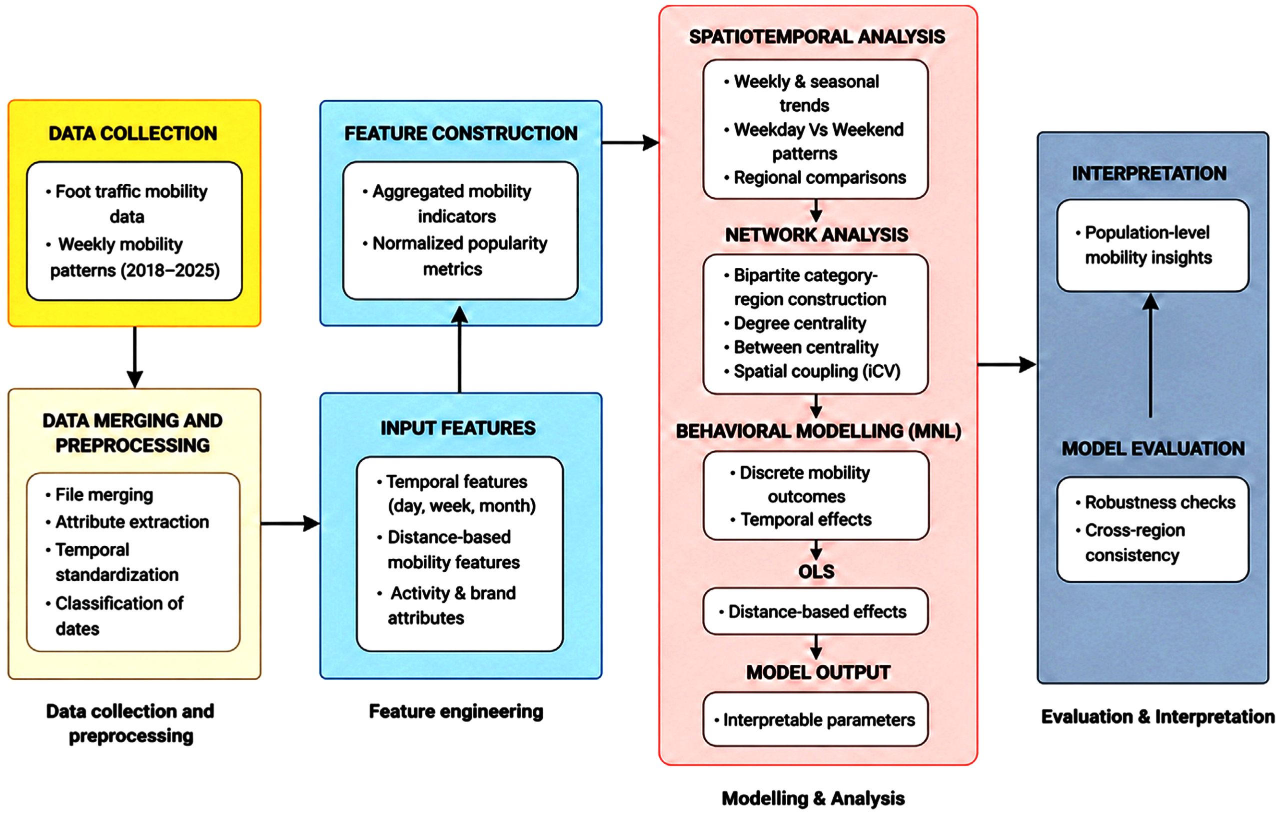

Figure 1. Proposed integrated workflow.

3.2. Data Preprocessing

Before model development, comprehensive preprocessing was undertaken on the dataset to ensure that the data is consistent, accurate, and ready for analysis. Temporal data is standardized to make the date columns consistent, create new features for year, month, week, and day of the week, etc., for the dataset.

The raw dataset was originally stored in individual files for each month of each calendar year, so first of all, it is necessary to merge all of them to create complete annual data sets, after which they needed to be concatenated in order to create one united data set of mobility data ranging from 2018 to 2025.

Nested and semi-structured data for temporal activity patterns, recorded as JSON format strings for daily foot traffic counts, are decoded to structured numeric format, for example, "Monday": 5, "Tuesday": 5, "Wednesday": 5, … Daily foot traffic counts are then segregated to individual weekday counts, which allow for the analysis of foot traffic patterns for specific weekdays, *i.e.*, weekends, as well as other specific periods of the week. Also, the individual brand-level foot traffic counts recorded in JSON format, for example, "Walmart": 24, "McDonald's": 9, "Hospitals": 5, are decoded to individual brand-level counts, with missing records being treated as empty records, to allow for the analysis of foot traffic patterns for individual brands, including the ones for which the foot traffic counts are missing or invalid.

3.3. Feature Engineering

Feature engineering was a vital step in developing the analytical framework to analyze temporal as well as distance-based patterns of human mobility using aggregated foot traffic datasets. The aim was to identify and construct features that are effectively captured when individuals travel, how far they move from their homes, and how their activity patterns change with location and time, while ensuring consistency across regions and years.

1) Brand to Category Mapping: The mapping between brand and category was performed using a hybrid rule based classification framework across individual brands and points of interest (POIs), which were segmented into higher-level functional activity categories such as: Retail, Restaurant, Healthcare, Automotive Dealerships, Recreation, Gas Station, Lodging, Transportation & Logistics, Education, Government & Public Services, Financial Services, Personal Care Services. This included lowercasing text, removing punctuation, whitespace normalization, and harmonization of keywords to standardize brand names. Classification rules were mostly based on keyword matching along the lines of industry semantics and business functionalities. Brands related to supermarkets, department stores, and convenience stores would be assigned Retail; hospitals, clinics, and pharmacies Healthcare; restaurants, cafés, and fast-food stores Restaurant; freight companies, airports, and places where people assembled for travel operations and delivery services to Transportation & Logistics.

In addition, to derive the mobility intensity profiles for each activity category, hourly stop count aggregates h00 to h23 are used to identify peak and non-peak movement times and to account for temporal variation in activity participation.

Ambiguous POIs, which have reasonable claims to belong to more than one category, were resolved through a hierarchical decision process. I began by identifying the predominant operational function of the POI using brand description and contextual business activity. If any uncertainty remained, the POI was assigned to represent its main consumer-facing function; for instance, a retail store containing a pharmacy section was categorized as Retail unless healthcare services dominated. POIs with insufficient description, conflicting codes, or overly generic names were assigned to an “Other” category to avoid any classification bias or the inflation of numbers in certain categories.

2) Feature Screening and Selection: Each dataset had a multitude of features that described mobility patterns as well as other contextual attributes, such as weekly visit counts, stops made by individuals daily as well as by hour, day of week activity distribution, distance from home, dwell times, device origin, as well as brand-level visit data, among others. To understand the interdependence between these features and their relationship with mobility outcomes, an exploratory cor-

relation analysis was performed using Pearson correlation coefficients. Highly collinear variables with absolute correlation coefficients exceeding |0.90| were considered redundant, and one representative variable was retained based on interpretability and completeness. Based on this correlation, strong correlations were observed between overall visit intensity, as well as temporal features such as weekday-weekend patterns, peak day activity, and visit behavior, as well as distance from home features, indicating the importance of considering these two dimensions of mobility. Variables with near-zero variance, excessive missingness, or constant values across observations were removed as they contributed minimal explanatory information. Categorical features with extremely sparse representation were consolidated into broader groups or excluded where appropriate to avoid unstable estimates during modeling.

Feature relevance was further evaluated through the Multinomial Logit modeling framework, which assessed the stability and interpretability of retained features across all 18 activity categories. Results consistently confirmed that temporal features demonstrated the strongest and most consistent contributions to differentiating mobility behavior across destination types. Distance-based mobility behavior was examined separately through an OLS regression model in which distance from home served as the continuous dependent variable, with activity category, U.S. state, and year as categorical predictors. Full model results for both the Multinomial Logit (MNL) and Ordinary Least Squares (OLS) specifications are reported in the Results section.

Using the results of the feature evaluation, it has been possible to develop a new set of features that are most relevant and suitable to understand and analyze human mobility behaviors. The new set of features that is most relevant and suitable to understand and analyze human mobility behaviors is as follows:

- Temporal features that help in understanding and analyzing the rhythms of movement and distinguish between weekday and weekend movements.
- Distance-from-home features that help in understanding and analyzing the constraints of accessibility and reach of daily activities.
- Brand-level activity features derived from the category mapping framework to differentiate mobility behavior across functional destination types.

3) Aggregation and Sample Reduction: Following the brand-to-category mapping and feature construction procedures outlined above, individual brand-level records were grouped into 18 functional activity categories, which served as the unit of analysis for behavioral modeling. The raw dataset was at the individual brand level and contained around 15 million POI-week records, each observation indicating mobility activity in a specific named brand or point of interest on a weekly basis. This aggregation collapsed the brand-specific units of observations into weekly mobility profiles at the category-level, resulting in an analytical sample of 180,913 category-level observations down from more than 15 million brand-level records. Aggregated across the analytical period: 2018-2025, each observation in the data identifies total weekly mobility activity for a given functional

activity category. This category-level structure forms the unit of observation for the Multinomial Logit model mentioned, ensuring that the behavioral model operates on stable, consistently defined mobility profiles rather than noisy individual brand-level records.

3.4. Experimental Setup

The results were estimated using maximum likelihood estimation (MLE) in the stats models library. Model convergence was established after 8 iterations, and statistical significance was evaluated at the $\alpha = 0.05$ level throughout. An OLS regression model was estimated to examine the spatial determinants of distance-based mobility behavior, with distance from home serving as the continuous dependent variable. Each observation represents a POI-week record capturing the weekly aggregated mobility activity associated with a specific point of interest. Activity category, U.S. states, and year were entered as categorical predictors using dummy coding, with Automotive Dealerships as the reference activity category, Alaska as the reference state, and 2018 as the reference year. The OLS model was fitted on 256,519 POI-week observations using heteroskedasticity-robust standard errors (HC3 covariance type) to account for non-constant variance across the large observational sample. The likelihood ratio test was used to evaluate the joint significance of the MNL model, and F-tests were used for the OLS model.

The category-level Anchoring Index was calculated using visit-weighted distance measures, differentiating between residential and daytime anchor contributions during weekday and weekend periods. Temporal decomposition was used to identify peak and off-peak mobility behaviors across hours of the day and days of the week. All modeling and index construction procedures were consistently applied across all 50 states and all years from 2018 through 2025 to ensure regional and temporal comparability. For the MNL, pseudo R^2 was reported alongside likelihood ratio testing for joint significance of predictors. For the OLS, R^2 and adjusted R^2 were used to assess model fit. Robustness of findings was evaluated through cross-regional consistency checks to verify the geographical stability of results across states.

Statistical computations, performance evaluation, and visualization were performed using numpy, pandas, matplotlib, and dask packages. The latter was selected for its ability to handle out-of-memory computation given the large analytical sample spanning approximately 15 million raw records across 2018-2025.

3.5. Model Development

This study proposes an anchoring-based mobility modeling framework to characterize variations in human population-level temporal/distance-based movement patterns. The framework combines a formally defined Anchoring Index, visit-weighted distance aggregation, temporal decomposition (weekday vs. weekend and peak vs. off-peak), and network-based representations to measure the extent to which activity categories are spatially anchored in residential and daytime locations. Instead of assuming that sample choice models can predict individual-level mobility behavior, the framework uses aggregated mobility data to extract structural patterns of mobility across categories, regions, and time, yielding interpretable metrics such as spatial dependence, the burden of dislocation, and network connectivity in large-scale human movement systems.

1) Anchoring Index Formulation: To measure how population mobility organizes space around residential and daytime activity centers, we propose an Anchoring Index (AI) that characterizes the relative strength of home-based versus daytime-based travel for various kinds of activity.

Let each mobility observation aggregate visitation from a population of devices to destination category c, with distances associated with two reference anchors:

- The residential anchor (home location), and
- The primary daytime anchor (typically associated with work or routine daytime activity).

For each activity category c, we compute visit-weighted average distances:

$$\bar{d}_{\text{home},c} = \frac{\sum_{i \in c} w_i d_{\text{home}}(i)}{\sum_{i \in c} w_i} \tag{1}$$

where $d_{\text{home}}(i)$ denotes the distance traveled from the home anchor, $d_{\text{day}}(i)$ denotes the distance traveled from the primary daytime anchor, w_i represents visit intensity (weighted stop counts), and the summation is taken over all observations i associated with activity category c.

The Anchoring Index for category c is then defined as:

$$AI_c = \bar{d}_{\text{home},c} - \bar{d}_{\text{day},c} \tag{2}$$

This formulation yields a continuous anchoring metric with an intuitive interpretation where,

- $AI_c > 0$ indicates activity categories primarily anchored around residential locations,
- $AI_c < 0$ indicates activities more strongly tied to daytime or work-related anchors.
- $AI_c \approx 0$ indicates spatially balanced or flexible activity patterns.

2) Temporal Decomposition of Anchoring: To capture temporal variation in spatial anchoring, the Anchoring Index was computed separately across multiple temporal regimes: Weekday vs Weekend.

- Weekday visits reflect routine commuting and work-related mobility.
- Weekend visits capture discretionary and leisure-driven travel.

Peak vs Off-Peak Hours

- Peak hours correspond to typical commute and activity surges.
- Off-peak hours reflect flexible, non-routine travel behavior.

For each temporal subset, category-specific Anchoring Indices were recalculated using the same weighted formulation, allowing direct comparison of how anchoring strength shifts across time.

3) Category-Level Distance Profiling: Using the Anchoring Index as the foundational metric, each activity category was further characterized by:

- Weighted average distance from home
- Weighted average distance from daytime anchor
- Total visitation volume

This produces a distance profile for each category, enabling differentiation between:

- Local routine activities (short distances, strong home anchoring),
- Work-oriented activities (negative anchoring, daytime centric),
- Discretionary activities (long distances, weak anchoring).

4) Network Construction and Analysis: Based on the aggregated foot traffic dataset, a bipartite category-region mobility network was constructed to explore structural relationships between activity categories and geographic regions. Nodes represent functional activity categories, or U.S. states, and each state is connected to every category when visits were recorded in that state for multiple participants. Edge weights were defined as the sum of visit volume aggregated across a category/state pair over the entire 2018-2025 analytical period. This resulted in a 75-node, 1043-edge network (density = 0.376) with moderate to high connectivity throughout the category-region network. I computed three network measures for each category node: a) degree centrality, quantifying the proportion of states connected to each category; b) betweenness centrality, which measures the extent to which a category node lies on shortest paths between other nodes, reflecting its bridging role in the network; and c) node strength, or total weighted visit volume across all connected states. Spatial coupling was assessed through the coefficient of variation (CV) of distance-from-home measures across states for each category, where elevated CV values reflect greater spatial dispersion in visitor origin, while lower values reflect spatially concentrated or locally anchored visitation patterns.

5) Behavioral Modeling (Multinomial Logit): Category-level mobility behavior was formally modeled through a Multinomial Logit (MNL) model with two groups of predictors. The unit of observation is a POI-week record, which are records of the aggregated mobility activity at each point of interest in a particular week. As for the outcome variable, it is a nominal functional activity family of the destination visited, which has 18 mutually exclusive mobility categories—Automotive Dealerships, Commercial & Trade Services, Community & Religious Services, Education, Financial Services, Funeral Services, Gas Station, Government & Public Services, Healthcare, Lodging, Mall, Other Personal Care Services, Pet Services, Recreation, Restaurant, Retail, Transportation & Logistics.

Three factors explain why the MNL framework is suitable for this analysis. This is first the dependent variable is nominal, while there is no natural ordering across activity categories that would meet the foundational requirement of MNL over ordered alternatives. Second, the aggregated population-level foot traffic records on which the model operates, rather than individual-level discrete choices, are especially useful for characterizing systematic behavioral patterns across large observational samples. Third, by using a class of conditional logit models with category-specific coefficient structure (as in the MNL), we can directly compare the effects of temporal sensitivity and activity intensity for each of the 18 mobility categories together and preserve interpretability at the population level.

The model included three fixed explanatory variables: hour-of-day, capturing the linear time-of-day effect on category-level mobility; hour^2, a quadratic term to capture non-linear temporal patterns that show their peak over midday and then dropping in the evenings; log-transformed total stops, normalized on a log-scale to reflect overall activity intensity. Maximum likelihood estimation: Converged after 8 iterations. (183,913 observations on 18 features); of class "hlm" Joint statistical significance is confirmed by the likelihood ratio test (LLR $p < 0.001$), and a pseudo-R^2 of 0.093 is observed, in line with expectation for population-level aggregated mobility data whilst controlling for individual-level heterogeneity. This amount of explanatory power is permissible for MNLs examining multi-category behavioral outcomes in large/heterogeneous observational samples.

Table 1 presents coefficient estimates, standard errors, z-statistics and 95% confidence intervals for all 18 relatively non-reference categories; coefficients are estimated with high precision across all categories (standard errors range from 0.006 to 0.113), reaffirming the statistical stability possible with such a large analytical sample. In most categories, all three predictors are statistically significant at the $\alpha = 0.05$ level. Two categories show no significant temporal coefficients (Community & Religious Services: hour: $p = 0.077$, hour^2: $p = 0.123$; and Healthcare, hour: $p = 0.517$, hour^2: $p = 0.570$). And these results are interpretable—Community & Religious Services visits cluster on days of the week (weekends vs. weekdays) rather than hours of a day, and Healthcare visits cluster around scheduled appointments and medical needs, which are negligible determinants for hour-of-day choice, letting time-of-day be a relatively weak predictor for both destination types. Table 1 reports 95% confidence intervals alongside standard errors and z-statistics for all category specific estimates showing that the effects reported in our main plots are stable and precise, as reflected in small 95% confidence intervals.

Table 1. Multinomial logit model estimates for category-level mobility behavior.

Category	Const	SE	Hour	SE	Hour^2	SE	Log Stops	SE
Automotive Dealerships	−1.9674	0.081	−0.0748	0.008	0.0027	0.000	0.1986	0.007
Commercial & Trade Services	2.5413	0.081	0.1618	0.011	−0.0058	0.000	−0.3985	0.008
Community & Religious Services†	0.0709	0.079	0.0156	0.009	−0.0006	0.000	−0.0353	0.007
Education	2.0996	0.070	0.0937	0.008	−0.0034	0.000	−0.2390	0.007
Financial Services	4.7138	0.070	0.2599	0.009	−0.0094	0.000	−0.6546	0.007
Funeral Services	−2.6913	0.083	−0.0994	0.008	0.0036	0.000	0.2679	0.007
Gas Station	2.6120	0.069	0.1171	0.008	−0.0043	0.000	−0.3000	0.006
Government & Public Services	−2.2356	0.081	−0.0844	0.008	0.0030	0.000	0.2251	0.007
Healthcare†	0.1320	0.075	0.0054	0.008	−0.0002	0.000	−0.0141	0.007

Continued

Lodging	−5.4155	0.092	−0.1875	0.008	0.0068	0.000	0.5156	0.008
Mall	3.4583	0.068	0.1625	0.008	−0.0059	0.000	−0.4133	0.006
Other	4.7706	0.068	0.2443	0.009	−0.0089	0.000	−0.6247	0.006
Personal Care Services	3.5176	0.068	0.1662	0.009	−0.0060	0.000	−0.4247	0.006
Pet Services	−0.4698	0.076	−0.0179	0.008	0.0006	0.000	0.0486	0.007
Recreation	−4.2967	0.088	−0.1532	0.008	0.0055	0.000	0.4171	0.008
Restaurant	−10.3892	0.113	−0.3178	0.009	0.0115	0.000	0.9260	0.009
Retail	4.1025	0.068	0.2081	0.009	−0.0075	0.000	−0.5176	0.006
Transportation & Logistics	0.6566	0.073	0.0283	0.008	−0.0010	0.000	−0.0710	0.007

SE = standard error. †Indicates statistically insignificant categories at $\alpha = 0.05$. N = 180,913 POI-week observations. Pseudo-R^2 = 0.093. LLR p-value < 0.001.

4. Results and Discussions

4.1. Descriptive Spatiotemporal Patterns

Population-level mobility derived from the 2018-June 2025 foot traffic dataset exhibits strong temporal regularity and meaningful regional variation across activity categories. The average hourly mobility profile, shown in Figure 2 (Average Hourly Mobility Profile by Category), reveals a pronounced diurnal structure. Across nearly all categories, activity levels remain low during early morning hours (00:00-05:00), increase steadily beginning around 07:00, and peak between approximately 15:00 and 17:00. Following the late-afternoon peak, mobility gradually declines into the evening. This inverted U-shaped pattern indicates that human movement is highly structured within predictable daily rhythms rather than randomly distributed throughout the day.

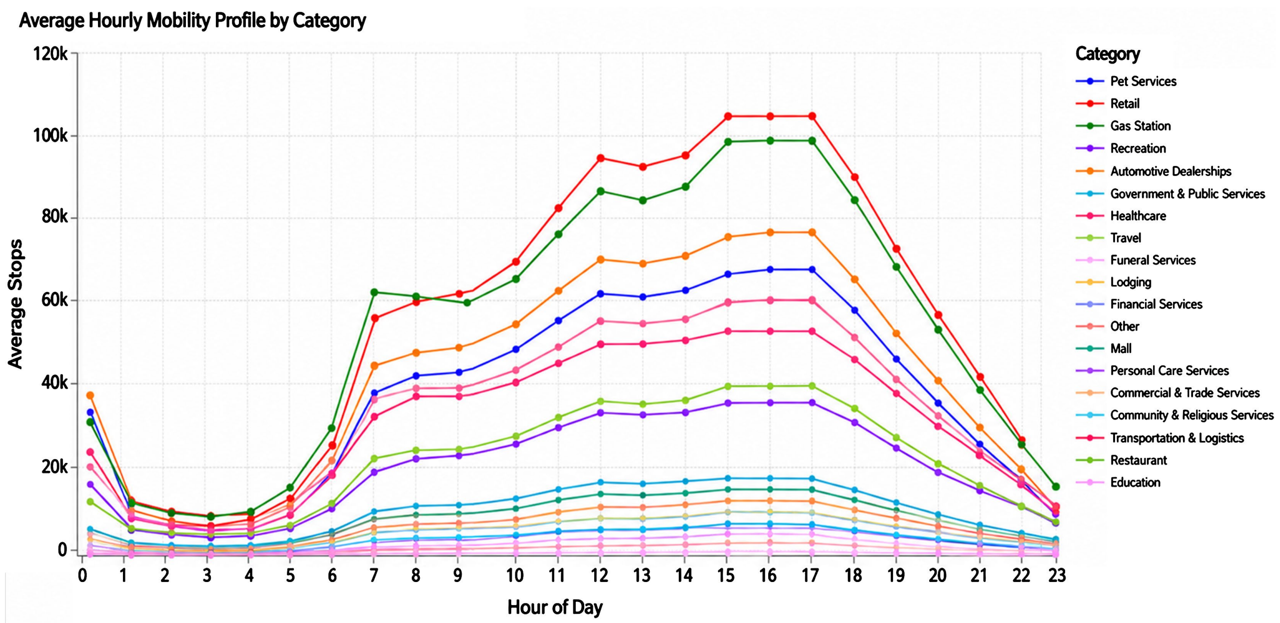

Figure 2. Average hourly mobility profile by category.

Despite the shared diurnal structure, substantial heterogeneity exists across categories. Retail, Restaurant, and Mall exhibit the highest overall intensity and the most pronounced afternoon peaks, suggesting strong alignment with commercial and leisure-oriented activity cycles. In contrast, Education and Healthcare demonstrate narrower activity windows and relatively earlier stabilization during the afternoon. Categories such as Community & Religious Services and Funeral Services show comparatively lower hourly variation, indicating weaker sensitivity to hour-of-day dynamics. These differences confirm that temporal mobility behavior varies systematically according to activity type.

Long-term temporal trends further highlight category-level divergence. As illustrated in Figure 3 (Category Mobility Trends Over Years, 2018-2025), several high-intensity categories particularly Retail, Mall, and Restaurant display marked growth between 2022 and 2024, reflecting substantial post-2022 expansion in commercial mobility activity. Health-care and Commercial & Trade Services also demonstrate upward trajectories during this period. The observed decline in 2025. across several categories likely reflects partial-year data coverage rather than structural contraction. Overall, these multi-year patterns indicate both recovery and expansion dynamics in key economic sectors.

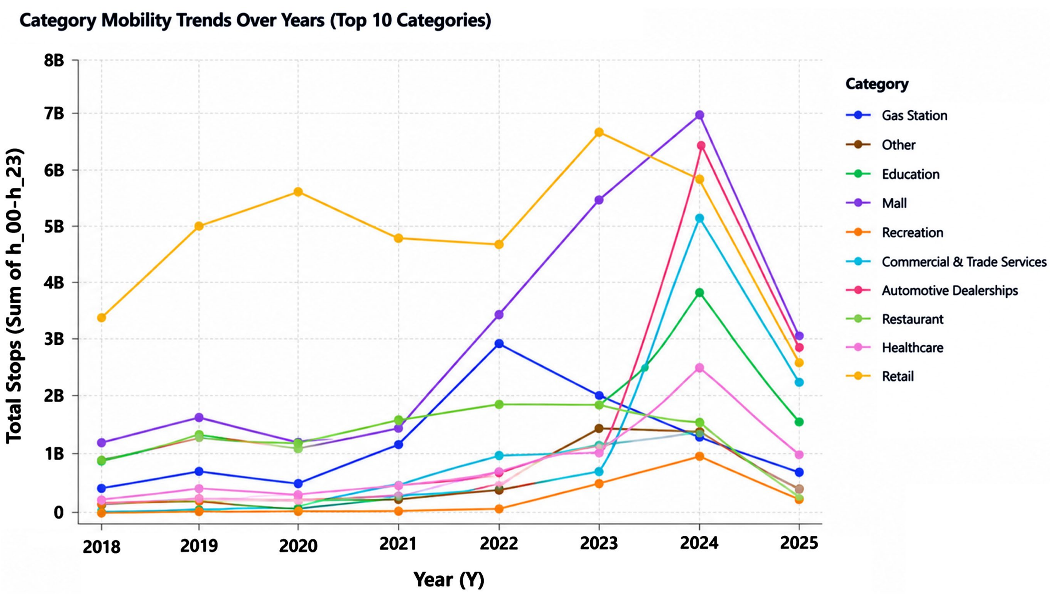

Figure 3. Category mobility trends over years (Top 10 categories).

In addition to temporal variation, mobility intensity differs significantly across regions. Figure 4 (Mobility Intensity by Selected Categories OverTime: CA, NC, TX, KS, CO, FL) compares total stop volumes across six states. Texas and Florida consistently exhibit higher aggregate mobility intensity relative to North Carolina and Kansas, while California shows moderate but stable growth over time. Although the general temporal trajectory remains broadly similar across states, absolute activity levels vary considerably, indicating that regional context plays a significant role in shaping overall mobility intensity.

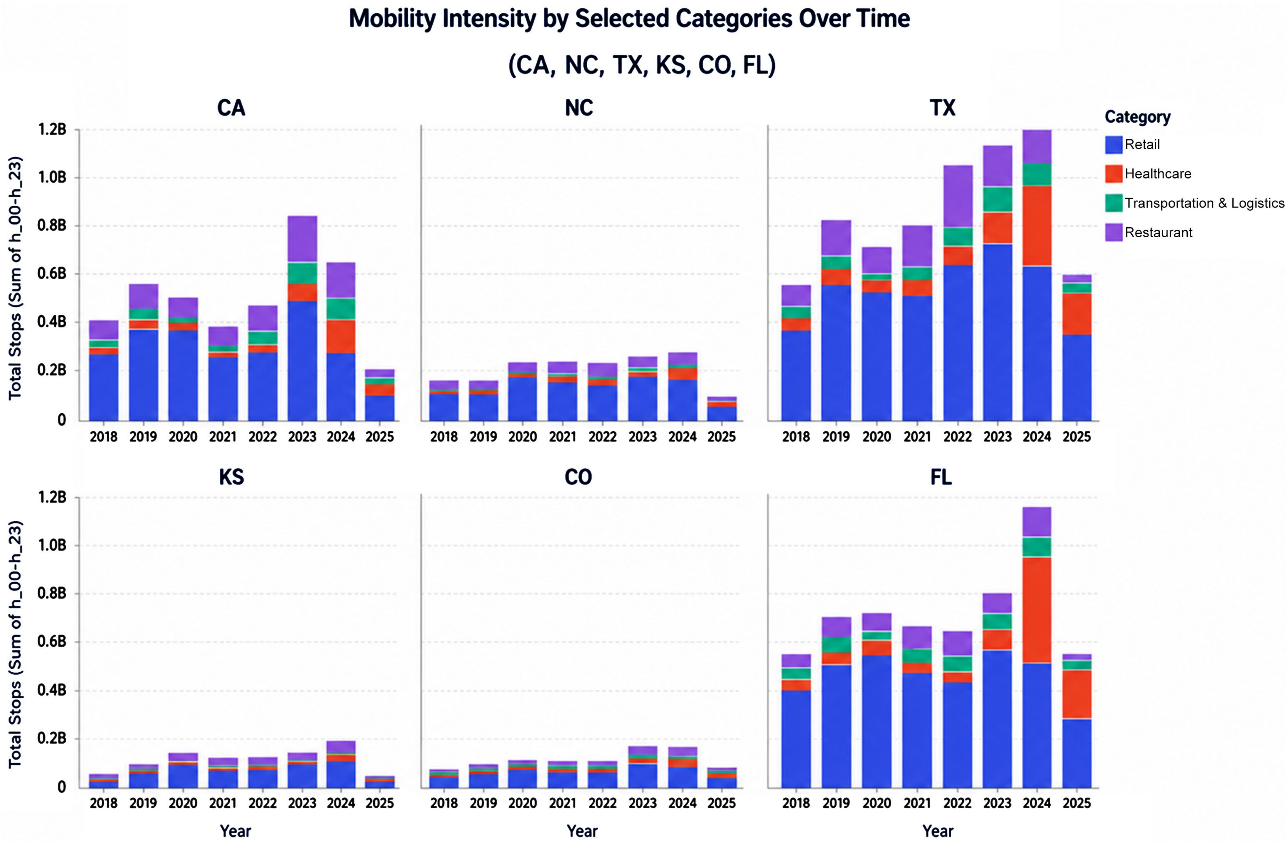

Figure 4. Mobility intensity by selected categories over time (CA, NC, TX, KS, CO, FL).

Taken together, Figures 1-3 demonstrate that human mobility exhibits strong daily temporal regularity, sustained multi-year growth in key commercial categories, and meaningful regional heterogeneity. These descriptive spatiotemporal patterns provide the empirical foundation for subsequent analyses examining activity intensity, spatial distance characteristics, and behavioral determinants of category-level mobility outcomes.

4.2. Activity Intensity and Weekly Structure

Beyond hourly and annual dynamics, overall activity intensity and weekly structure provide additional insight into category-level mobility behavior. Figure 5 presents a comparison of average weekly visits by category, disaggregated into weekday and weekend totals. Clear differences emerge across activity types, indicating that mobility is not uniformly distributed across the week.

Education exhibits the highest overall weekly volume, with a strong dominance of weekday activity, reflecting institutional schedules and structured daily routines. Mall and Retail also show substantial total visits, but with a comparatively larger weekend contribution, consistent with discretionary and leisure-oriented shopping behavior. Restaurants demonstrate high activity across both weekday and weekend periods, suggesting its dual role in routine daily consumption and social or recreational activity.

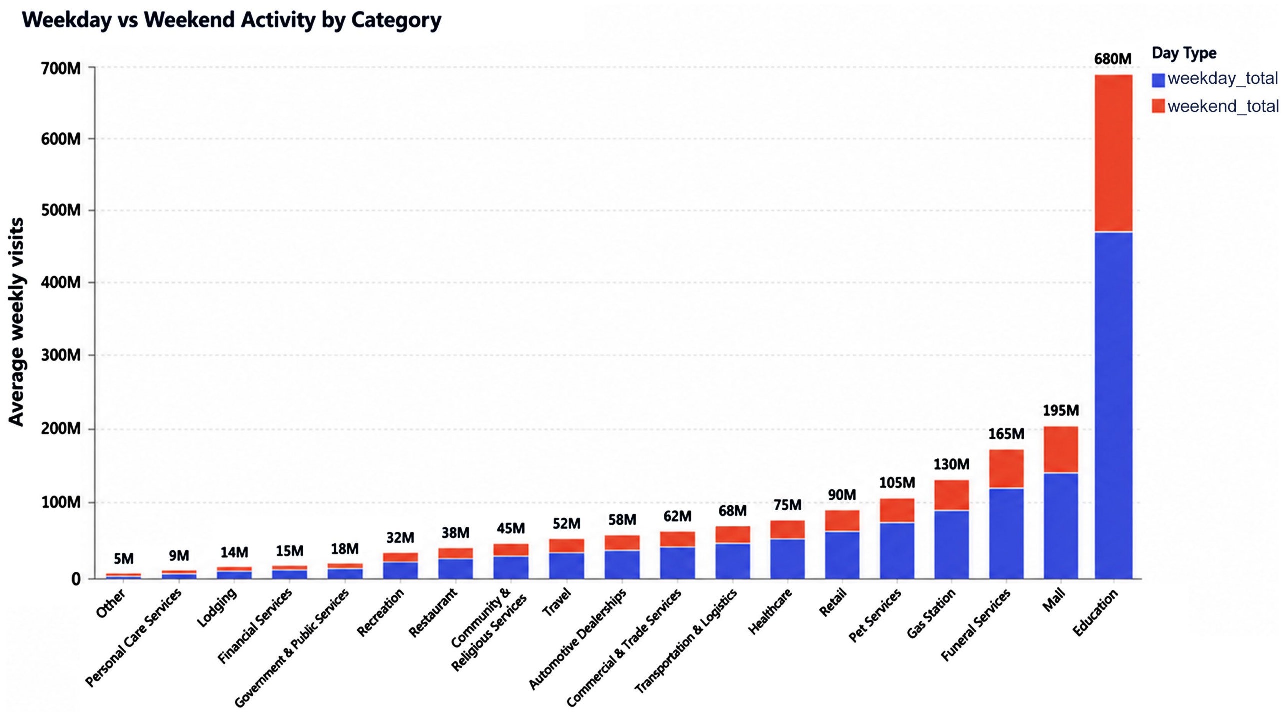

Figure 5. Weekdays vs weekend activity by category.

Categories such as Gas Station and Financial Services display relatively stable weekday-dominated structures, reflecting essential and transaction-based mobility needs. In contrast, Recreation and Travel exhibit comparatively higher weekend shares, indicating discretionary temporal flexibility and non-work-related mobility.

The relative magnitude of category-level activity is further illustrated in **Figure 6**, which visualizes mobility intensity weighted by total daily stops. Larger word sizes correspond to higher aggregate mobility contributions over the study period.

Figure 6. Mobility intensity by category (Weighted by total daily stops).

As shown in Figure 6, Retail, Mall, and Restaurant dominate overall mobility intensity, reinforcing their central role in shaping aggregate foot traffic patterns. Automotive Dealerships and Healthcare also contribute substantially, while categories such as Funeral Services and Community & Religious Services represent comparatively smaller shares of total mobility. This concentration of activity within a limited set of high-intensity categories suggests that a small number of economic sectors account for a disproportionate share of population-level movement.

Together, the weekly distribution and intensity patterns indicate that mobility behavior reflects both structured institutional schedules and discretionary consumer activity. Categories with strong weekday dominance (e.g., Education and Financial Services) reflect routine-based movement, whereas categories with elevated weekend shares (e.g., Recreation and Travel) reflect flexible or leisure-driven mobility. These distinctions provide important context for understanding how temporal dynamics interact with spatial and behavioral determinants examined in subsequent sections.

4.3. Distance-Based Mobility Patterns

While temporal dynamics describe when mobility occurs, spatial distance characteristics reveal how far individuals travel and whether activities are locally anchored or spatially dispersed. The distribution of travel distances from home across categories is presented in Figure 7 (Distance from Home by Category).

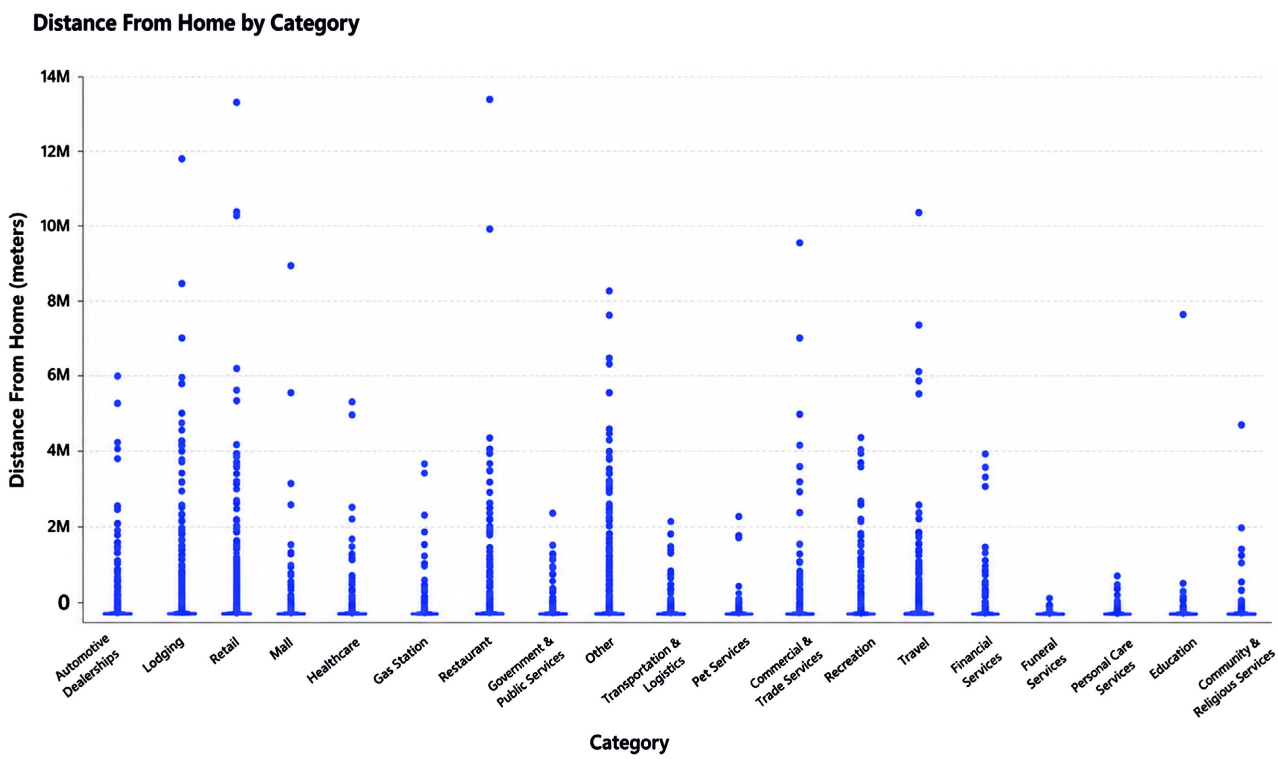

Figure 7. Distance from home by category.

As shown in Figure 7, most categories exhibit highly right skewed distance distributions, with the majority of visits occurring within relatively short distances from home but with occasional long-distance outliers. Categories such as Travel, Lodging, and Recreation display wider dispersion and higher extreme values, indicating greater spatial reach and longer-distance mobility behavior. In contrast, categories including Gas Station, Financial Services, and Personal Care Services demonstrate tighter clustering around shorter distances, suggesting localized, routine-oriented activity.

Retail, Restaurant, and Mall occupy an intermediate position. While a substantial proportion of visits occur close to home, these categories also exhibit moderate spatial dispersion, reflecting both neighborhood-level and destination oriented trips. This pattern suggests that commercial mobility combines localized convenience-based visits with longer distance, centralized activity hubs.

To further evaluate spatial anchoring behavior, Figure 8 (Home vs Daytime Anchoring by Category) compares the average difference between home-based and daytime locations across categories. Positive values indicate categories more closely associated with home-origin activity, whereas negative values reflect stronger association with daytime or work-based spatial contexts.

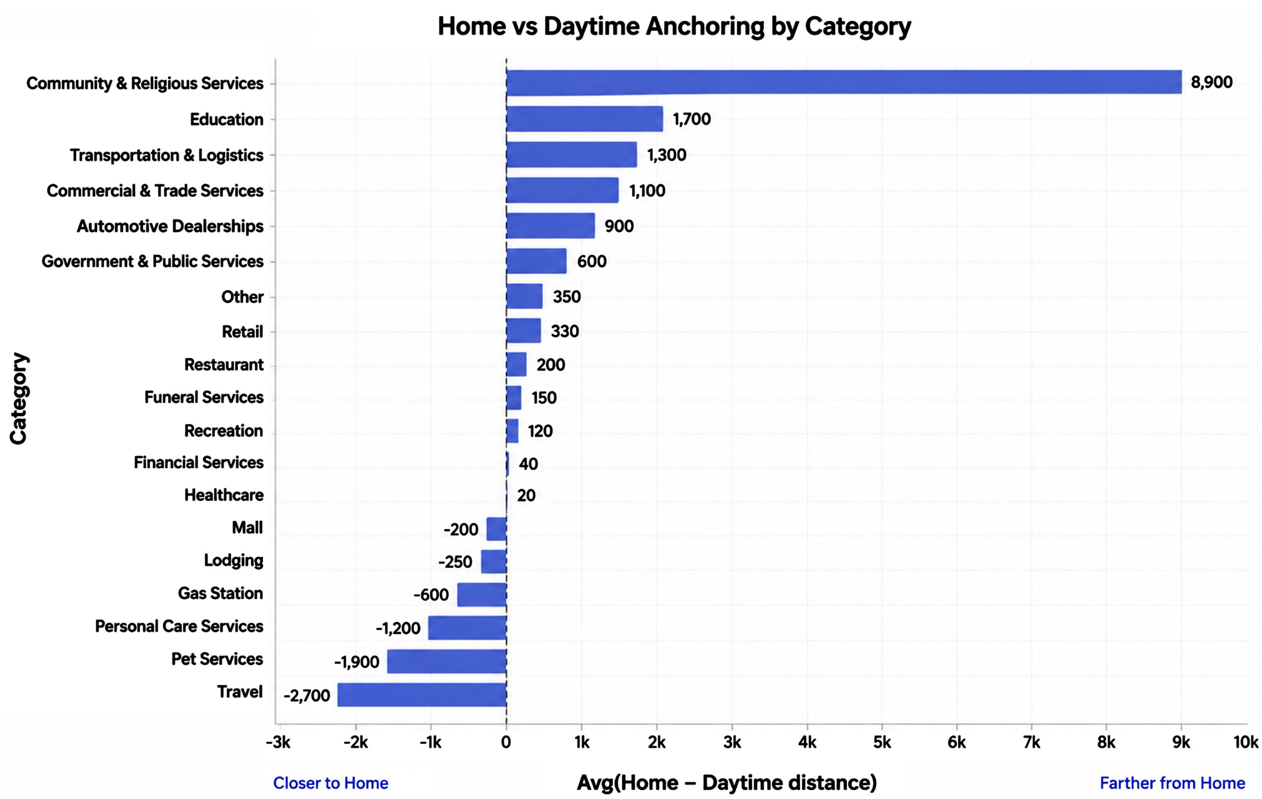

Figure 8. Home vs daytime anchoring by category.

The anchoring analysis reveals distinct spatial roles across categories. Community & Religious Services and Education exhibit strong positive home anchoring, indicating that visits are typically concentrated within residential proximity. Government & Public Services and Commercial & Trade Services also demonstrate moderate home association.

In contrast, Travel and Pet Services show pronounced negative anchoring values, suggesting stronger alignment with daytime or non-residential spatial contexts. Restaurant and Retail appear closer to neutral anchoring, reflecting their dual function as both neighborhood-based and destination based activities. Mall and Lodging similarly display balanced or mildly negative anchoring, consistent with centralized commercial or hospitality destinations.

Collectively, these spatial findings indicate that mobility categories differ not only in intensity and timing but also in spatial reach and anchoring structure. Routine-service categories tend to exhibit localized, home-proximate behavior, whereas discretionary or destination-based categories display broader spatial dispersion. These distance-based distinctions complement the temporal patterns identified earlier and provide critical context for interpreting the behavioral modeling results presented in the following section.

Ordinary Least Squares Model: To examine the spatial determinants of mobility behavior, an OLS regression model was estimated with distance from home as the continuous dependent variable; full model specification details are provided in Section III (Experimental Setup). The model achieves an R^2 of 0.086, indicating that category, region, and year jointly explain approximately 8.6% of the variance in distance-from-home behavior, with the F-statistic confirming strong joint statistical significance ($p < 0.001$). While the proportion of explained variance is modest, this is consistent with expectations for population-level aggregated mobility data, where substantial within-category heterogeneity remains unexplained by category membership alone. Full coefficient estimates are reported in **Appendix**.

In **Appendix**, results reveal substantial heterogeneity in distance-from home behavior across activity categories relative to the Automotive Dealerships reference category. Lodging exhibits the largest positive distance effect ($\beta = 21,940$, SE = 1740, $p < 0.001$), followed by Transportation & Logistics ($\beta = 8325$, SE = 2908, $p = 0.004$) and Gas Station ($\beta = 4771$, SE = 1232, $p < 0.001$), confirming that these destination types attract visitors from the greatest distances relative to the reference category. In contrast, Funeral Services ($\beta = -9192$, SE = 1958, $p < 0.001$) and Personal Care Services ($\beta = -7033$, SE = 1205, $p < 0.001$) exhibit the largest negative effects, reflecting their strongly proximity-driven, residentially anchored demand patterns. Several categories, including Mall, Restaurant, Retail, Financial Services, Education, Government & Public Services, and Community & Religious Services, show no statistically significant difference in distance-from-home behavior relative to Automotive Dealerships ($p > 0.05$), suggesting broadly similar spatial reach across these destination types.

Temporal trends reveal a consistent increase in distance from-home mobility across years relative to the 2018 baseline. The largest positive deviation is observed in 2024 ($\beta = 15,790$, SE = 1044, $p < 0.001$), followed by 2025 ($\beta = 12,080$, SE = 899,

$p < 0.001$) and 2023 ($\beta = 6361$, SE = 745, $p < 0.001$), indicating a sustained post-pandemic expansion in mobility reach across activity categories. Notably, 2020 shows no statistically significant change from the 2018 baseline ($\beta = -231$, SE = 587, $p = 0.695$), consistent with the severe mobility restrictions associated with the COVID-19 pandemic that effectively suppressed distance-from-home travel to pre-study levels.

4.4. Behavioral Modeling Results (Multinomial Logit)

To formally quantify the determinants of category-level mobility behavior, a multinomial logit (MNL) model was estimated using hour-of-day, a quadratic time term (hour 2), and log-transformed total stops as explanatory variables. The model was fitted on 180,913 observations and converged successfully under maximum likelihood estimation. The likelihood ratio test indicates strong joint statistical significance ($p < 0.001$), and the model achieves a pseudo-R^2 of 0.093, reflecting meaningful explanatory power given the multicategory structure and large alternative set.

1) Temporal Structure: The temporal coefficients reveal systematic heterogeneity in time-of-day sensitivity across mobility categories. A large subset of categories including Commercial & Trade Services, Education, Financial Services, Government & Public Services, Mall, Personal Care Services, Retail, and Travel exhibit a positive linear hour effect combined with a negative quadratic term. This sign pattern indicates an inverted U-shaped relationship, consistent with pronounced afternoon peaks observed in the descriptive hourly profiles. These categories demonstrate strong alignment with structured daytime activity cycles and institutional schedules.

In contrast, categories such as Automotive Dealerships, Funeral Services, Lodging, Recreation, and Restaurant display a negative linear hour coefficient paired with a positive quadratic term. This configuration reflects a U-shaped or extended temporal pattern, suggesting relatively stronger activity during early or later portions of the day compared with midday concentration. Restaurant, in particular, exhibits one of the strongest nonlinear effects, indicating substantial deviation from conventional business hours concentration.

Healthcare and Community & Religious Services show comparatively weak or statistically insignificant temporal curvature, indicating more stable distributions throughout the day. These categories appear less governed by sharp diurnal peaks and more by routine or necessity-based demand.

2) Sensitivity to System-Wide Activity Intensity: The results indicate marked variation in intensity sensitivity across categories (Table 1). Restaurant exhibits the largest positive log-transformed total stops coefficient among all categories ($\beta = 0.926$, SE = 0.009, $p < 0.001$), followed by Lodging ($\beta = 0.516$, SE = 0.008, $p < 0.001$) and Recreation ($\beta = 0.417$, SE = 0.008, $p < 0.001$), demonstrating that these categories expand disproportionately during high-mobility periods. These activity types appear demand-amplified, gaining relative share when aggregate movement intensifies.

Conversely, Financial Services, Other, Retail, Mall, and Commercial & Trade Services display strong negative coefficients on log (total stops). This does not imply absolute decline during busy periods, but rather a relative redistribution effect: when overall mobility increases, intensity-driven categories (notably Restaurant and Recreation) capture a larger share of total activity. These business-oriented categories are thus more scheduled-driven than intensity-amplified.

Moderate positive effects are observed for Automotive ealerships, Funeral Services, and Healthcare, suggesting partial responsiveness to aggregate activity without the amplification observed for discretionary sectors.

3) Distinct Behavioral Patterns Across Mobility Categories: Taken together, the temporal and intensity effects reveal clear heterogeneity in category-level mobility behavior.

a) Schedule-Driven Categories: Education, Financial Services, Government & Public Services, Retail, and Mall exhibit strong afternoon peaks and comparatively weaker amplification under high system activity. These categories are primarily structured by institutional or business-hour routines.

b) Demand-Amplified Categories: Restaurant, Lodging, and Recreation show strong positive intensity sensitivity and nonlinear temporal patterns. These categories disproportionately expand during high-mobility periods and reflect discretionary or consumption-driven behavior.

c) Routine-Stable Categories: Healthcare and Community & Religious Services display limited curvature and modest intensity responsiveness, indicating more necessity-based and spatially anchored mobility.

d) Empirical Coherence Between Descriptive and Modeling Results: The modeling results align closely with the descriptive spatiotemporal patterns presented in Sections 4.1 - 4.3. Categories identified as intensity-amplified correspond to those exhibiting strong weekend shares and broader spatial dispersion, while schedule-driven categories mirror the structured afternoon peaks observed in the hourly mobility profiles. This consistency reinforces the robustness of the analytical framework and confirms that temporal dynamics and aggregate system intensity jointly shape category-level mobility behavior.

4.5. Network Analysis of Mobility Flows

1) Network Structure and Category Centrality: The systematic structural differentiation across activity types in connectivity, centrality, and visit strength is exposed by the category-region mobility network. Degree centrality, betweenness centrality, and node strength are listed for all 18 activity categories in **Table 2**.

Table 2. Category-region network centrality measures.

Category	Degree Centrality	Betweenness Centrality	Node Strength
Retail	0.757	0.941	4.82×10^{10}
Mall	0.743	0.004	2.10×10^{10}

Continued

Restaurant	0.743	0.000	1.17×10^{10}
Automotive Dealerships	0.757	0.000	1.11×10^{10}
Commercial & Trade Services	0.730	0.000	1.09×10^{10}
Gas Station	0.743	0.000	1.00×10^{10}
Education	0.757	0.000	8.47×10^{9}
Healthcare	0.757	0.027	7.58×10^{9}
Recreation	0.757	0.000	5.67×10^{9}
Lodging	0.743	0.000	3.88×10^{9}
Pet Services	0.730	0.000	3.07×10^{9}
Transportation & Logistics	0.743	0.000	1.46×10^{9}
Financial Services	0.730	0.000	1.20×10^{9}
Funeral Services	0.716	0.000	7.61×10^{8}
Government & Public Services	0.757	0.000	5.09×10^{8}
Community & Religious Services	0.716	0.000	3.84×10^{8}
Other	0.743	0.000	3.38×10^{8}
Personal Care Services	0.716	0.000	1.30×10^{8}

Note: Degree centrality is normalized by the total number of nodes in the category-region mobility network. Betweenness centrality is weighted by aggregated visit volume. Node strength represents the total aggregated visit volume across all connected states from 2018 to 2025.

Retail has the highest betweenness centrality (0.941) across all categories, meaning it is the largest bridging node in the category-region network; it connects essentially every state with a high volume of visits through retail as an entry. This is mirrored in the structure of Retail, the most ubiquitous type of Activity around different geophysical contexts. Healthcare (betweenness = 0.027) and Mall (betweenness = 0.0041), on the other hand, identify secondary bridging categories; while their visit frequencies are relatively low overall, they remain structurally significant in connecting diverse regional contexts. Most of the other categories have marginal values for betweenness centrality in a way that endorses this expectation (most of their regional connectivity lies in coarse, non-bridging spatiotemporal demand).

For node strength, Retail exhibits the highest weighted visit volume at 4.82×10^{10}, followed by Mall (2.10×10^{10}), Restaurant (1.17×10^{10}), Automotive Dealerships (1.11×10^{10}), and Commercial & Trade Services (1.09×10^{10}). These categories represent high-frequency and geographically dispersed mobility demands and collectively account for the majority of total network visit flow.

In contrast, Personal Care Services (1.30×10^{8}), Community & Religious Services (3.84×10^{8}), and Government & Public Services (5.09×10^{8}) exhibit substantially lower network strength values, reflecting their more localized and spatially bounded service functions within the human mobility network.

2) Spatial Coupling Analysis: The spatial coupling results in Lodging identifies a notable difference in the extent of visitor origins associated with each activity category Table 3.

Table 3. Distance-based mobility characteristics by category.

Category	Mean Distance (m)	Std Distance (m)	Spatial Coupling CV
Lodging	39,719	239,197	6.022
Community & Religious Services	24,799	195,899	7.899
Other	17,171	148,273	8.635
Education	16,886	211,097	12.501
Automotive Dealerships	17,350	116,529	6.716
Healthcare	10,999	94,435	8.586
Commercial & Trade Services	14,594	124,902	8.558
Financial Services	13,681	110,615	8.085
Retail	14,785	149,869	10.137
Mall	12,909	121,659	9.424
Restaurant	15,586	142,101	9.117
Recreation	19,820	125,549	6.334
Pet Services	11,917	79,613	6.681
Transportation & Logistics	10,212	142,013	4.701
Government & Public Services	24,425	120,979	4.953
Personal Care Services	8985	42,081	4.683
Gas Station	9328	90,089	4.661
Funeral Services	7494	25,878	3.453

Note: Mean Distance and Std Distance are reported in meters. Spatial Coupling CV represents the coefficient of variation describing the relative spatial variability of mobility patterns across categories.

Education has the highest spatial coupling CV (12.50) as the distance to home of visitors to this category varies widely between states, likely reflecting both local schools and long distance university destinations that share a common name space within the same category label. Following this, Retail (CV = 10.14) and Mall (CV = 9.42) form a similar pattern, as both types appear to serve the same functional need at the neighborhood level but also play a role as a regional destination type due to their geographic contextualization.

Both Lodging(mean = 39,719 m) and Community & Religious Services(mean = 24,799 m) have high mean distances likely related to their connection with overnight and long distance mobility. On the other hand, Personal Care Services (mean = 8985 m), Gas Station(mean = 9328 m), and Funeral Services (mean = 7494 m) have the lowest mean travel distances from home rank swell in line with their strongly residential-anchor dependent proximity-driven demand patterns.

The combined findings on category-region mobility flows reveal that the structural differentiation of connectivity and spatial reach is not limited to network centrality measures, but extends to both dimensions of category-region mobility flows; in particular, high-frequency and essential categories dominate network strength whereas discretionary orregional specialty categories exhibit greater variability in visitor origins at a given market share.

5. Limitations and Future Work

This study has a few limitations that deserve acknowledgment. First, reliance on aggregated and anonymized mobility data limits the opportunity to explore individual-level hetero geneity and heterogeneous mobility responses to contextual pressures. Trip chaining behavior, where multiple activities are linked within a single outing, is largely unobservable in the dataset, thereby hindering a fuller understanding of complex travel decision-making processes. This is a known constraint of POI-level aggregated foot traffic data and limits the extent to which the Anchoring Index can be interpreted as reflecting deliberate sequentiall mobility decisions rather than isolated destination visits. Second, spatial uncertainty emerges from distance measures based on inferred home and daytime anchors rather than true origins and destinations.

This limitation is most consequential for individuals whose schedules are irregular, who maintain multiple work sites, or whose activity patterns deviate substantially from the routine home-to-destination-and-back model assumed by the distance-from-homemetric. The OLS model, which uses distance from home as the dependent variable, inherits this limitation directly—coefficients reflect systematic category-level patterns in inferred distance rather than precisely measured travel distances, and should be interpreted accordingly. Third, the Anchoring Index, while effective at capturing aggregate mobility behavior at the level of activity categories and geographic regions, is insufficient to convey variation within categories or behavioral adjustments over short time scales driven by transient dynamics such as weather events, special occasions, or policy interventions.

The weekly aggregation structure of the Dewey Weekly Patterns+dataset further constrains the temporal resolution of the analysis, preventing examination of within-week behavioral dynamics at the daily or hourly level beyond what the hourly distribution variables permit. Fourth, the Multinomial Logit model specification is subject to the Independence of Irrelevant Alternatives (IIA) assumption, which requires that the relative probability of choosing between any two activity categories is unaffected by the presence or absence of other alternatives. This assumption may not hold in practice, given the functional overlap between certain destination types—for example, between Malland Retail, or between Healthcare and Personal Care Services—potentially introducing bias in category-specific coefficient estimates. Future work should consider nested logit or mixed logit specifications to relax this assumption. Fifth, while the study covers all 50 U.S. states over seven years from 2018 through 2025, the data set reflects mobility patterns captured through opt-in location based applications, which may not be fully representative of all demographic groups. Populations with lower rates of smart phone ownership or location services adoption—including elderly individuals, lower-income households, and rural residents—may be systematically underrepresented, potentially limiting the generalizability of findings to these groups. Finally, the brand-to-category mapping process, while systematic and rule-based, introduces classification uncertainty for ambiguous POIs. Despite the hierarchical decision process applied to resolve ambiguous cases, some misclassification is inevitable at the margins, particularly for multi-function destinations such as big-box retailers with pharmacy or fuel services. This uncertainty propagates into all category-level analyses, including the Anchoring Index, OLS model, MNL model, and network analysis.

Having addressed these limitations, there are at least three key avenues in which future research can extend this framework. Multi-anchor representations may afford more complex modeling of individual mobility because work, recreation hubs, and other important activity locations extend beyond home-based patterns. Representing mobility within a multi-anchor system, where individuals are the mean between their residential, occupational, and recreational anchors would greatly increase the explanatory power of the Anchoring Index and bring it closer to reflecting whole bounded daily travel behavior complexity.

Although longitudinal modeling approaches would be useful for understanding the evolution of anchoring behavior over time, including how mobility patterns change from week to week, month to month, and year to year as individuals move through different life contexts. The current dataset—which has data for 2018 to 2025 (the period covering the COVID-19 disruption) over seven years—is well-suited for such analyses. This finding joins the ordinal characterization of minimal behavioural disruption during 2020, as denoted by a non-significant distance coefficient in its OLS model, in confirming that this dataset is well adapted to capturing significant yet underlying structural breaks present in the behaviour.

The next big step is to start integrating external contextual data. Mobility data connected with land use, transit supply, socioeconomic, and health indicators has the potential to conduct better causal analysis as well as equity-driven accessibility evaluations. Including weather, special event calendar, and transport policy datasets would further enable researchers to separate short-term changes in behavior from long-term trends and structures of mobility—a limitation explicitly acknowledged in this study. The extra context would be especially useful for a more nuanced examination of how the day-of-week effects in extreme weather, major sporting or cultural events, and transit service disruptions impact distance-from-home behavior across activity categories.

In the sense of network modeling, a category-region bipartite network framework is proposed here and could be extrapolated into dynamic multilayer graph representation that allows for coupling of temporal, distance-based, and activity-based interactions within the mobility system. For example, connectivity, centrality and spatial coupling between categories can be tracked across regions—capturing things such as collapse of network strength in the Lodging sector during COVID-19, and recovery that followed. Unifying transit, walking, and driving layers into a single mobility network structure could enable multilayer representations to capture even more complementary mode uses as multimodal travel behavior can be analyzed at the population level.

More advanced machine learning methods can further extract more subtle patterns of complex spatiotemporal mobility data. Keyword-Neural network, Graph neural networks, Attention-based sequence model. Trajectory representation learning with neural that can capture nonlinear temporal dependencies and cross-category interaction effects that cannot be detected in the current linear MNL and OLS specifications. These methods could be viewed, then, as potential complements (rather than direct replacements) of the proposed interpretable anchoring framework—functioning to diagnose segments or details in an individual's behavior that merit additional investigation through the lens of anchoring.

Finally, the anchoring-based metrics can be developed into predictive or simulation models with a lot of applied potential. This recommendation is aimed at enhancing scenario analysis capabilities to inform bicycle transportation planning through assessing infrastructure changes, policy interventions, and emergency response. One particularly important frontier is urban resilience assessment—analyzing mobility networks' response to sharp shocks (e.g., natural disaster, pandemic, transit service interruption). Overall conclusions. Based on the network centrality findings from this study and the mapping of bridges between categories and regional contexts, it appears that disruptions to high-centrality category-region interface nodes (bridging nodes), such as those identified in this study (e.g., Retail was dominant across all regional boundaries), may produce a disproportionately large systemic effect on overall mobility network function. Together, these paths will allow the anchoring based framework to be a practical, extensible, and policy relevant base for data-driven urban planning, emergency preparedness, and sustainable mobility governance.

6. Conclusions

In summary, this study offers a key contribution to the understanding of population-level human movements through presenting a spatial anchoring framework to jointly capture temporal and distance-based behavior. The framework moves away from more conventional mobility metrics based on such simple measures of trip frequency, instead measuring the extent to which activities agglomerate near residential and daytime anchors over space and time through the creation/implementation of a continuous Anchoring Index. The empirical patterns show that mobility is neither homogeneous nor random, but instead differs systematically by activity type, time period, and geography, and reflects the underlying social economics and functional urban processes.

The analytical framework developed in this study to characterize population-level mobility behavior has four complementary components. I show that anchored patterns between residential and daytime anchors differ greatly depending on the essentiality of an activity, meaning that both ground truth visit distributions and two approaches to measuring spatial dependence across anchor types are important for understanding built environment impacts on behavior. Second, weekday-weekend and peak-off-peak comparisons provide a spatiotemporal decomposition that captures the temporal heterogeneity of mobility behavior to multiple hourly patterns within and across days. Third, using a Multinomial Logit model, the temporal determinants of activity category choice are independently characterized across all 18 destination types and hour-of-day/intensity systematically delineate mobility patterns (by broad category). Fourth, an OLS regression model investigates the distance characteristics of mobility behavior and finds that destination types like Lodging, Transportation & Logistics, and Gas Station have very long reach, while Funeral Services, Personal Care Services, and Healthcare demonstrate more proximity-driven demand patterns consistent with residential anchoring. The peak of the temporal coeffecient for 2020 is not statistically different, in fact virtually indistinguishable from that of 2018 baseline, suggesting empirical evidence for what has been an ongoing hypothesis about the suppressive effect of COVID-19 on distance-from-home mobility and the sustained rise observed from 2021 through to as late as 2024, representing a continuous post-pandemic level restoration and expansion in how far urban populations could spatially extend.

The paper also constructs a region-region network representation of mobility flows, representing bidirectional edges connecting states with a weight reflecting the volume of visits between each category and state. Analysis of the topological structure shows that network is dominated by Retail with very high betweenness centrality (0.941), which acts as a most related node across the whole regions, followed by Healthcare acting as secondary structural connectors (**Figure 4(b)**). Moreover, spatial coupling analysis also indicates that highly localized, proximity driven demand characteristics are typical for Funeral Services and Gas Stations as evidenced by the low corresponding spatial coupling coefficients; whereas Education and Retail locations show the most variable visitor origin distances by state reflecting their role as both local and regional-segment destinations. These network-based results collectively underscore the structural differentiation and interdependencies of mobility flows across connectivity and spatial reach dimensions, permitting a much more robust characterization of category-region interlinkages than distance metrics alone.

Considering weighted distance metrics, weekday-weekend and peak-off-peak comparisons, network-based representation types, and behavioral modeling as integral components of the framework reveals not only how much people move but also where and when their activities are located in space. Such distinction is important to determine if populations are anchor-dependent or exhibit flexible mobility behavior, and thus relevant for transportation planning, accessibility assignment, equity evaluation, and investment decisions in infrastructure.

Notably, the proposed framework is scalable, explicit and interpretable—which are essential characteristics that will help communicate with planners and policymakers. Instead, the Anchoring Index generates a metric based on data that is interpretable and can directly be implemented in real-world planning situations unlike black-box predictive models. Adding to this interpretability, the network based representations show the structural geography of whether a category-region pair contains more (regionally distributed) or less (spatially concentrated) all traffice types for mobility flows. With activity-sensitive clustering and spatial limitations of where individuals can physically reach, the framework targets data-driven solutions that improve access to opportunities and create a fairer and more robust urban mobility systems.

More generally, it closes the gap between agent-level behaviors and aggregate models of urban systems, showing that human behavioral patterns have significant regularities at the population scale discoverable from anonymized foot traffic data aggregated over populations. The study also shows that these regularities hold for 50 U.S. states and across a seven-year analytical span that includes the COVID-19 disruption years 2018 through 2025, further validating the robustness and temporal generalizability of the anchoring-based framework. With growing pressure due to congestion, equity, and sustainability challenges, cities need actionable insights from large-scale mobility data. The heuristic anchored approach discussed in this work, combined with network analysis and additional behavioral and distance modelling that expand knowledge generated through such an approach, offers a realistic yet extensible outline for how these types insights may be systematically created communicated and used to foster fairer more accessible and resilient urban mobility systems.

Conflicts of Interest

The author declares no conflicts of interest regarding the publication of this paper.

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Appendix

Table A1. OLS regression results for distance from home.

Variable	Coef.	SE	z	p
Commercial & Trade Services	1419.92	1207.21	1.18	0.240
Community & Religious Services	2150.30	6024.96	0.36	0.721
Education	−7888.49	5240.82	−1.51	0.132
Financial Services	−1648.11	1514.88	−1.09	0.277
Funeral Services	−9192.39	1958.02	−4.70	0.000
Gas Station	4770.79	1232.27	3.87	0.000
Government & Public Services	367.18	2291.63	0.16	0.873
Healthcare	−4523.21	1175.67	−3.85	0.000
Lodging	21940.00	1740.35	12.61	0.000
Mall	−504.38	1379.36	−0.37	0.715
Other	2614.51	1106.24	2.36	0.018
Personal Care Services	−7033.37	1205.34	−5.84	0.000
Pet Services	−3379.54	1601.98	−2.11	0.035
Recreation	3046.09	1326.23	2.30	0.022
Restaurant	−696.95	1147.87	−0.61	0.544
Retail	−1327.60	1021.75	−1.30	0.194
Transportation & Logistics	8325.24	2907.59	2.86	0.004
AL	−2.473e+05	1.26e+04	−19.60	0.000
AK	Reference	-	-	-
AZ	−2.374e+05	1.27e+04	−18.76	0.000
AR	−2.465e+05	1.26e+04	−19.55	0.000
CA	−2.287e+05	1.27e+04	−17.99	0.000
CO	−2.401e+05	1.26e+04	−19.00	0.000
CT	−2.469e+05	1.26e+04	−19.52	0.000
DE	−2.455e+05	1.26e+04	−19.45	0.000
FL	−2.437e+05	1.26e+04	−19.36	0.000
GA	−2.463e+05	1.26e+04	−19.54	0.000
HI	−6.852e+04	1.74e+04	−3.94	0.000
IA	−2.509e+05	1.26e+04	−19.91	0.000
ID	−2.413e+05	1.27e+04	−18.95	0.000
IL	−2.496e+05	1.26e+04	−19.76	0.000
IN	−2.498e+05	1.26e+04	−19.81	0.000

Continued

KS	−2.523e+05	1.26e+04	−20.01	0.000
KY	−2.482e+05	1.26e+04	−19.69	0.000
LA	−2.451e+05	1.26e+04	−19.44	0.000
MA	−2.438e+05	1.27e+04	−19.13	0.000
MD	−2.488e+05	1.26e+04	−19.71	0.000
ME	−2.391e+05	1.27e+04	−18.83	0.000
MI	−2.405e+05	1.27e+04	−19.01	0.000
MN	−2.475e+05	1.26e+04	−19.60	0.000
MO	−2.493e+05	1.26e+04	−19.76	0.000
MS	−2.472e+05	1.26e+04	−19.60	0.000
MT	−2.394e+05	1.28e+04	−18.76	0.000
NC	−2.466e+05	1.26e+04	−19.55	0.000
ND	−2.495e+05	1.26e+04	−19.77	0.000
NE	−2.504e+05	1.26e+04	−19.85	0.000
NH	−2.472e+05	1.27e+04	−19.53	0.000
NJ	−2.474e+05	1.26e+04	−19.60	0.000
NM	−2.334e+05	1.27e+04	−18.41	0.000
NV	−2.365e+05	1.27e+04	−18.58	0.000
NY	−2.400e+05	1.27e+04	−18.94	0.000
OH	−2.504e+05	1.26e+04	−19.84	0.000
OK	−2.495e+05	1.26e+04	−19.83	0.000
OR	−2.427e+05	1.27e+04	−19.18	0.000
PA	−2.488e+05	1.26e+04	−19.70	0.000
RI	−2.473e+05	1.26e+04	−19.57	0.000
SC	−2.402e+05	1.26e+04	−19.05	0.000
SD	−2.463e+05	1.26e+04	−19.53	0.000
TN	−2.460e+05	1.26e+04	−19.52	0.000
TX	−2.477e+05	1.26e+04	−19.65	0.000
UT	−2.346e+05	1.27e+04	−18.50	0.000
VA	−2.465e+05	1.26e+04	−19.51	0.000
VT	−2.427e+05	1.26e+04	−19.24	0.000
WA	−2.310e+05	1.28e+04	−18.07	0.000
WI	−2.492e+05	1.26e+04	−19.74	0.000
WV	−2.477e+05	1.26e+04	−19.64	0.000
WY	−2.360e+05	1.27e+04	−18.58	0.000

Notes: Dependent variable is *DISTANCE_FROM_HOME*. HC3 robust standard errors reported. Alaska serves as the reference state.