Human Mobility in Helsinki: Predicting Next Locations and Exploring Spatial Segregation Patterns

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Supervisor: Dr Stephen Law

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Abstract

The prevalent use of smartphones and location-based services has led to the creation of large-scale mobility datasets. Predicting human mobility has become increasingly important for applications such as urban planning, traffic optimisation, and public health monitoring. While many models focus on spatiotemporal patterns, this study highlights the value of incorporating social context, particularly the concept of experienced segregation, into next-location prediction. Utilizing a novel dataset from Locomizer, this thesis makes two main contributions. First, it introduces a novel adaptation of the Schelling model to simulate avoidance behaviour using a real urban road network in Helsinki, rather than a traditional grid format. Second, it evaluates the effect of segregation-related features on the performance of three recurrent neural network (RNN) models: GRU4Rec, ST-RNN, and DeepMove. The results show that while there are improvements associated with the segregation features, these gains are relatively small, ranging from 0.01 to 0.08 percentage points in Acc@1. This suggests that although the inclusion of socio-spatial context is conceptually valuable, more substantial performance improvements may require further hyperparameter tuning or the adoption of alternative advanced architectures. In conclusion, this research offers a new perspective on the integration of social behaviour and mobility prediction. It provides a methodological foundation for incorporating segregation-aware features into machine learning models and demonstrates the potential relevance of these features for understanding mobility patterns.

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1 Introduction

1.1 Background

The widespread use of smartphones and location-based services, alongside advances in Internet of Things (IoT) technologies and sensors, has led to the generation of vast repositories of mobility data collected from diverse sources. In parallel, the rapid expansion of social networks such as Twitter, Facebook, and Foursquare has introduced a new type of spatiotemporal data enriched with contextual layers, including text, images, videos, user preferences, and activity histories. The combination of abundant mobility data and the growing capabilities of artificial intelligence (AI) and machine learning (ML) methods presents a unique opportunity for researchers to advance the task of human mobility prediction (Nezhadettehad et al., 2025; Chekol and Fufa, 2022; Luca et al., 2021).

Human mobility prediction plays a crucial role in numerous domains. It supports urban planning (Vallejos et al., 2025; Huang et al., 2024; Dao, Le and Yoon, 2019; Cornacchia and Pappalardo, 2021), traffic optimisation (Gibbs, Eggo and Cheshire, 2023; Wang et al., 2019), and public health interventions, particularly those focused on monitoring disease transmission (Huang et al., 2024; Nezhadettehad et al., 2025). While these efforts primarily rely on spatiotemporal features such as location sequences and time intervals, recent studies argue that mobility prediction can benefit from incorporating additional contextual signals, particularly those related to social interaction and exposure (Nezhadettehad et al., 2025; Aoudjit et al., 2013). One promising dimension of context is experienced segregation, which refers to how individuals expose themselves to others who are either socially or economically similar or dissimilar. Rather than focusing solely on where individuals go, this approach also considers whom they are likely to encounter. Recent work suggests that these patterns of social exposure may offer predictive value, as individuals' decisions are often shaped not only by distance and time but also by their preferences for certain types of social environments (Liao et al., 2025; Hong et al., 2023).

In this regard, the Schelling simulation offers a useful behavioural framework. Originally developed to explain residential segregation, the model demonstrates how even moderate preferences for similar neighbours can result in highly segregated spatial patterns (Schelling, 1971; Singh, Vainchtein and Weiss, 2009; Elkind et al., 2019; Avetisov et al., 2018). Schelling's insight was that large-scale segregation can emerge from small-scale decisions. However, most applications of this model remain focused on residential contexts and are limited to grid-based environments. To the best of the author's knowledge, there has been little effort to extend this logic to urban mobility or to examine how individual preferences for certain social environments influence route choices.

Adapting Schelling-style logic to dynamic mobility offers an opportunity to explore how behavioural preferences might shape everyday movement. Simulating how individuals avoid or seek out specific types of environments could produce valuable behavioural signals to inform next-location prediction models. These simulations could serve as a pre-training step or provide features that reflect latent social dynamics within the urban fabric.

In terms of prediction, several existing next-location prediction models have attempted to incorporate social influence, primarily by inferring social ties from mobility trajectories.

Mutual information and co-location patterns are often used to identify individuals whose movement is highly correlated, under the assumption that social connections drive spatial proximity (Cho, Myers and Leskovec, 2011; Bapierre, Jesdabodi and Groh, 2015). While this approach captures individual-level influence, it does not measure broader exposure to dissimilar or similar groups. To the best of the author's knowledge, no studies have explicitly tested whether the degree of social or economic similarity among people encountered during daily mobility can enhance next-location prediction.

Additionally, most existing studies on mobility-based segregation focus on the United States or the United Kingdom, with an emphasis on descriptive spatial patterns rather than predictive modelling (Athey et al., 2021; Gao, Zhong and Wang, 2024). Finland, and particularly the Helsinki metropolitan area, remains significantly underexplored in this literature. Only a small number of studies have addressed next-location prediction in the Finnish context, and these have tended to ignore the social dimensions of mobility altogether. Although residential segregation in Helsinki is relatively low compared to other European capitals, there has been a gradual increase since the early 2000s, particularly along socioeconomic and ethnic lines (Tunström and Wang, 2019). These trends are further reinforced by selective mobility patterns, where higher-income and Finnish-born residents are more likely to avoid areas perceived as disadvantaged, while foreign-born residents often relocate based on affordability and access to housing (Karhula et al., 2020).

1.2 Aims and objectives

This thesis addresses several key gaps in the literature on spatial segregation and human mobility prediction. First, it proposes a novel adaptation of the Schelling model to simulate socio-spatial avoidance behaviour over a realistic urban road network, moving beyond the conventional use of static, grid-based environments. Second, it introduces a set of segregation-related features that are embedded into machine learning models for improving next-location prediction.

The study is guided by the following objectives:

- Simulate how micro-level behavioural preferences, expressed through Schelling-inspired tolerance thresholds, can generate macro-level patterns of segregation in daily mobility;
- Evaluate whether incorporating the experienced segregation metrics of individuals encountered along mobility routes improves the accuracy of next-location prediction models.

By addressing these objectives, the thesis aims to contribute both conceptually and methodologically to the field of mobility prediction. It highlights the importance of embedding socio-spatial context, particularly experienced segregation, into predictive frameworks. This approach offers a new way to interpret movement patterns in relation to social dynamics, with potential implications for urban policy and planning in Helsinki and other cities facing similar challenges.

2 Literature Review

2.1 Next Location Prediction

Human mobility prediction plays a crucial role in a wide range of applications, including urban planning (Vallejos et al., 2025; Huang et al., 2024; Dao, Le and Yoon, 2019; Cornacchia and Pappalardo, 2021; Luca et al., 2021; Nezhadettehad et al., 2025), telecommunication (Hai, Nguyen and Thai-Nghe, 2016; Hong et al., 2023), traffic optimisation (Gibbs, Eggo and Cheshire, 2023; Wang et al., 2019; Chekol and Fufa, 2022), transportation systems (Hong et al., 2023; Nezhadettehad et al., 2025), advertising (Xue et al., 2021; Hai, Nguyen and Thai-Nghe, 2016), location-based recommendation systems (Cho, Myers and Leskovec, 2011; Luca et al., 2021), criminal investigation (Hai, Nguyen and Thai-Nghe, 2016), and public health monitoring such as disease spread prediction (Gibbs, Eggo and Cheshire, 2023; Huang et al., 2024; Nezhadettehad et al., 2025). Given its broad range of applications, individual-level mobility data has become one of the most valuable sources for understanding human behaviour in space and time.

Recent advances in smartphone technology and location-based sensors, along with the widespread use of location-based social networks, have significantly expanded the availability of mobility data. Such data typically consist of spatio-temporal records that capture the movement of individuals over a defined observation period. These records are commonly collected through electronic devices and structured as trajectories, where each entry includes a user identifier, geographic coordinates, and a timestamp (Nezhadettehad et al., 2025; Luca et al., 2021). Researchers then use these trajectories to reconstruct individual movement patterns, which serve as the basis for next-location prediction models.

Several model families have been developed to address this task. Markov models were among the earliest approaches, relying on transition probabilities between locations derived from users' historical check-ins (Krumm, 2008; Froehlich and Krumm, 2008). While computationally efficient and intuitive, they are limited in their ability to capture long-term dependencies (Nezhadettehad et al., 2025). Recurrent Neural Networks (RNNs) offer an improvement in this regard by modelling sequential data and learning spatiotemporal patterns from user trajectories (Liu et al., 2016; Feng et al., 2018; Luo, Liu and Liu, 2021). However, traditional RNNs struggle with retaining long-range dependencies, especially when dealing with sparse or irregular sequences (Luca et al., 2021; Lun et al., 2025).

More recent approaches have explored transformer-based models, which use self-attention mechanisms to capture dependencies across time steps. These models have shown strong performance in sequential tasks (Hong, Martin and Raubal, 2022; Lin et al., 2021), but they often require large training datasets and can underperform in underrepresented regions or demographic groups if the training data are not sufficiently diverse (Corrias, Gjoreski and Langheinrich, 2023; Wang and Osaragi, 2024). Graph Neural Networks (GNNs) present another powerful alternative, capable of modelling non-Euclidean structures such as road networks or user–POI graphs. GNNs can effectively learn high-dimensional representations and integrate both spatial and temporal information (Capanema et al., 2023; Lei et al., 2025; Kim et al., 2021). However, their adoption remains limited in practice due to their high computational complexity and memory requirements (Yu et al., 2024).

Despite the rapid progress in model development, accurately predicting an individual's next location remains a challenging task. In addition to capturing the spatiotemporal regularities in human behaviour, models must also account for a wide range of contextual factors that influence individual mobility decisions (De Domenico, Lima and Musolesi, 2013). One such factor is social context. People often move through space in ways that reflect their interactions with others, whether through intentional meetings, workplace proximity, or shared activity spaces. Incorporating this dimension into prediction models may improve performance, particularly when linked to mobility-based segregation patterns (Wang et al., 2011; Nezhadettehad et al., 2025).

2.2 Mobility Segregation

The segregation literature has traditionally focused on residential patterns, examining how individuals' home locations are unevenly distributed across neighbourhoods based on social attributes such as race, ethnicity, and income. However, most studies that estimate neighbourhood effects often overlook daily mobility, implicitly assuming that an individual's exposure to social environments is confined to their place of residence. This static view fails to capture the complexity of spatial segregation in everyday life, where activities frequently occur beyond the boundaries of residential areas (Liao et al., 2025; Ravalet, 2006; Athey et al., 2021; Hedman et al., 2021; Kwan, 2013; Moro et al., 2021).

In practice, individuals might experience segregation through their mobility as they move between residential areas, workplaces, schools, and leisure spaces. These interactions may involve exposure to both similar and dissimilar social groups (Ubarevičienė, van Ham and Tammaru, 2024). A key driver of this process is homophily, the tendency for people to associate with others who share similar backgrounds. This is further shaped by individual utility-maximising behaviour, where people seek to minimise effort and maximise satisfaction based on their socioeconomic conditions (Schneider et al., 2013). Consequently, daily activity demands and lifestyle preferences lead to different levels of experienced segregation.

For instance, individuals who engage in frequent social activities, such as shopping, weekend outings, or visits to cafés, may encounter more diverse social groups and thus experience greater social integration. In contrast, visits to restaurants, entertainment venues, or exclusive spaces may correlate with higher levels of segregation, as these places often cater to specific income groups and may exclude others through pricing or cultural norms (Liao et al., 2025; Tóth et al., 2021; Avetisov et al., 2018; Nilforoshan et al., 2023; Ravalet, 2006; Hong et al., 2023). Over time, these behavioural patterns can lead to the spatial clustering of individuals with similar characteristics in specific activity locations, reinforcing broader patterns of socio-spatial segregation. This type of behavioural sorting is referred to in this study as an "affinity profile" (Ubarevičienė, van Ham and Tammaru, 2024).

In summary, experienced segregation can be defined as the cumulative level of separation that an individual encounters, shaped by both the people they live near and the people they encounter during daily activities. It reflects the interaction between residential location, travel behaviour, and the spatial distribution of activities that make up an individual's activity space (Liao et al., 2025).

2.3 Schelling Simulation

One of the most widely used approaches for analysing spatial segregation is the Schelling simulation. Thomas Schelling originally proposed a simple spatial model to demonstrate how, even under relatively tolerant individual preferences, an integrated city can evolve into a segregated one. His core insight was that segregation can emerge not necessarily from strong discriminatory intent, but rather from moderate preferences for having similar neighbours. In the classic Schelling model, agents of two types are placed on a grid or line and are considered "satisfied" if a minimum proportion (t) of nearby neighbours within a certain distance (w) are of the same type. Unsatisfied agents are allowed to either move to empty locations or swap places with others. These micro-level decisions can produce highly segregated macro-level patterns, even when the threshold t is relatively low (Schelling, 1971; Singh, Vainchtein and Weiss, 2009; Elkind et al., 2019; Avetisov et al., 2018; Zakine et al., 2024; Clark and Fossett, 2008).

The Schelling model is often used to illustrate how homophily, or the preference for similar others, can generate emergent patterns of social sorting. This same principle is relevant when examining experienced segregation in daily mobility. In this context, Schelling-inspired simulations can be adapted to explore how individual preferences for particular social or economic environments influence the routes people take. The author argues that these simulations offer valuable exploratory tools for uncovering the collective spatial patterns that may emerge from individual-level behavioural rules. Furthermore, the outcomes of such simulations may be useful as inputs for next-location prediction models, helping to incorporate socially grounded behavioural logic into data-driven approaches.

However, the Schelling simulation is still mostly conducted in grid format and focuses on residential segregation. There are some modifications of the Schelling model, such as its application in a graph format introduced by Banos (2012). Other adaptations are more related to mobility, including a version with mobility distance constraints that requires agents to select locations based on realistic spatial proximity by Gambetta, Mauro and Pappalardo (2023). There is also the Social-EPR model by Moro et al. (2021), which uses Schelling-inspired logic to calculate the probability of a user visiting a new place. Therefore, a key gap remains in adapting Schelling-style simulations to explore how individual preferences for specific social or economic environments influence the routes people choose to take. The next section builds on this insight by reviewing how mobility prediction models have attempted to incorporate social exposure, and why experienced segregation may be a critical but missing dimension in these approaches.

2.4 Next Location Prediction with Experienced Segregation Context

Several next-location prediction models have incorporated exposure to others, particularly by inferring social ties to improve mobility forecasting. These models often use mutual information to identify pairs of individuals whose mobility patterns are strongly correlated. Instead of relying solely on an individual's location history, the prediction also incorporates the movement trajectories of others with high mutual information scores, under the assumption that socially connected individuals often exhibit spatial-temporal proximity (De Domenico, Lima and Musolesi, 2013; Pan et al., 2012; Wang et al., 2011; Crandall et al., 2010; Yi et al., 2017; Wang et al., 2019) The social connected inference in these models typically involves analysing co-location patterns. For example, Cho, Myers and Leskovec (2011) identify social ties based on repeated check-ins within 25 km of another user's home.

Building on this, several models have formalised social influence within mobility prediction. The Socio-Spatial-Temporal PPM (SOST-PPM) by Bapierre, Jesdabodi and Groh (2015) extends spatial-temporal models by introducing both synchronous social influence (when friends co-visit locations) and broader social trends. Similarly, the Periodic Mobility Model (PMM) developed by Cho, Myers and Leskovec (2011) was extended into the Periodic & Social Mobility Model (PSMM), which integrates network-based social influence. In PSMM, the likelihood of a user visiting a location is influenced by the recency and proximity of a friend's check-in, thus capturing both temporal and spatial social dynamics. However, to the best of the author's knowledge, no existing studies have examined whether the degree of exposure to similar or dissimilar individuals during daily mobility can enhance next-location prediction models.

2.5 Next Location Prediction in Helsinki

While a number of studies have explored individual-level segregation and mobility patterns in countries such as the United States (Athey et al., 2021) and the United Kingdom (Gao, Zhong and Wang, 2024), these investigations primarily focus on descriptive spatial analysis rather than predictive modelling. In contrast, Finland remains notably underrepresented in the literature on next-location prediction. Only a few studies have addressed this context, and even those largely overlook the social dimensions of mobility, particularly experienced segregation. For instance, Laasonen (2005) applied sequence-matching techniques similar to Markov models for route prediction based on cellular data in Helsinki. Laukkanen et al. (2008) used CrimeStat® III to generate spatial estimates of likely offender locations from crime incident data in the Greater Helsinki area, while Qin et al. (2012) employed transition probabilities from smartphone-based data to model movement in southern Finland. Although methodologically valuable, these studies remain limited in scope, focusing on technical prediction rather than integrating social exposure or segregation-related dynamics into their models.

This omission is particularly significant in light of Finland's evolving urban and demographic landscape. Although levels of residential segregation in Helsinki are still relatively low compared to other major European cities, they have shown a gradual upward trend since the early 2000s, especially along socioeconomic and ethnic lines (Tunström and Wang, 2019). Socioeconomic disadvantage has become increasingly concentrated in specific neighbourhoods characterised by higher unemployment rates, lower education attainment, and a higher proportion of foreign-language-speaking residents. Concurrently, higher-income groups are becoming more spatially concentrated, contributing to growing polarisation within the city. Since the late 1990s, the professionalisation of the workforce has further contributed to patterns of residential stratification, particularly in the Helsinki capital region (Rosengren et al., 2024).

Crucially, patterns of selective mobility have been identified as a key driver of emerging segregation. Karhula et al (2020) argued that Finnish-born residents are more likely to avoid relocating to areas perceived as socially or economically disadvantaged, particularly neighbourhoods associated with lower-performing schools. Conversely, residents with an immigrant background are more likely to move into areas with higher shares of foreign-born populations, often influenced by affordability and housing market constraints rather than a preference for ethnic clustering. These contrasting patterns suggest that mobility itself plays a formative role in the production of segregation, further underscoring the importance of incorporating social exposure and mobility-driven mechanisms into next-location prediction models within the Finnish context.

2.6 Research gap

Building on the literature reviewed, this study addresses several key gaps in current research. First, although Schelling-inspired simulations are widely used to model residential segregation, they have rarely been adapted to investigate how individual preferences for particular social or economic environments influence the routes people take. Most existing models are static and grid-based, limiting their ability to reflect the dynamic and spatially realistic nature of daily mobility. Second, while some next-location prediction models incorporate social exposure, they tend to focus on mutual information between highly correlated individuals rather than measuring the degree of exposure to similar or dissimilar groups encountered in terms of economic background and the level of attraction a user has on a certain affinity category during everyday movement. As a result, they overlook the broader socio-spatial environment that shapes experienced segregation.

This thesis aims to address several research gaps by focusing on Helsinki, a city where socio-spatial segregation is growing but remains underexplored within the domain of predictive mobility modelling. To the best of the author's knowledge, no existing next-location prediction studies in this context have incorporated segregation-related features. This study presents two key contributions. First, it leverages high-resolution and novel GPS-based mobility data from Locomizer to simulate Schelling-style mobility avoidance behaviour using a realistic road network rather than an abstract grid. Second, it introduces a novel approach to embedding experience segregation metrics into recurrent neural network (RNN) models for next-location prediction. For this purpose, the author adopts three RNN-based architectures: GRU4Rec, ST-RNN, and DeepMove. While a detailed justification for this model selection is provided in the Methodology chapter, RNNs were chosen because they offer a balance between simplicity and complexity.

3 Methodology

3.1 Overview

This study begins with data cleaning and preprocessing for both the simulation and next location prediction analysis. From the cleaned dataset, the author develops a Schelling-inspired simulation to explore socio-spatial avoidance in urban mobility. At the core of this simulation is a threshold-based routing mechanism, where users are modelled as agents who selectively avoid road segments predominantly used by individuals from the opposite income group.

For the next-location prediction task, three recurrent neural network (RNN)-based models are employed: GRU4Rec, ST-RNN, and DeepMove. The performance of each model is evaluated in two configurations: (1) a baseline version trained using standard spatiotemporal inputs, and (2) a modified version that incorporates additional segregation-related features. The rationale behind choosing these models, along with the integration of segregation metrics, is detailed in the subsequent sections.

Before introducing the modelling architecture, the following section presents the Locomizer GPS dataset, describes the logic behind its structure, and outlines the key preprocessing steps undertaken to prepare the data for analysis. A summary of the research design is illustrated in Figure 1.

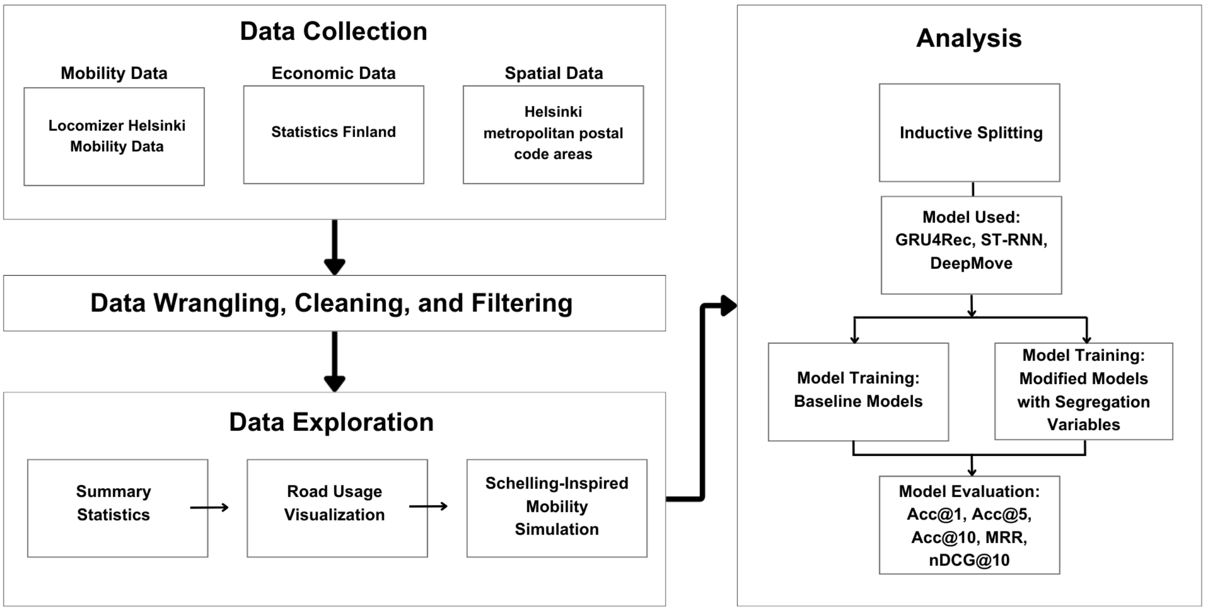

Figure 1: Research Framework.

3.2 Locomizer Dataset

3.2.1 Affinity Profile Algorithm

The primary dataset used in this study was obtained from Locomizer, a UK-based data service company that licenses anonymised mobile GPS data collected from over 200 mobile applications. This data is pre-processed to ensure compliance with relevant privacy regulations, including the General Data Protection Regulation (GDPR). Specifically, this research uses Locomizer's Audience Profiles, with a focus on the Footfall and Brand Affinity datasets, to model human mobility patterns and infer socio-spatial dynamics in the Helsinki metropolitan region (Locomizer, 2021; Zhong et al., 2024).

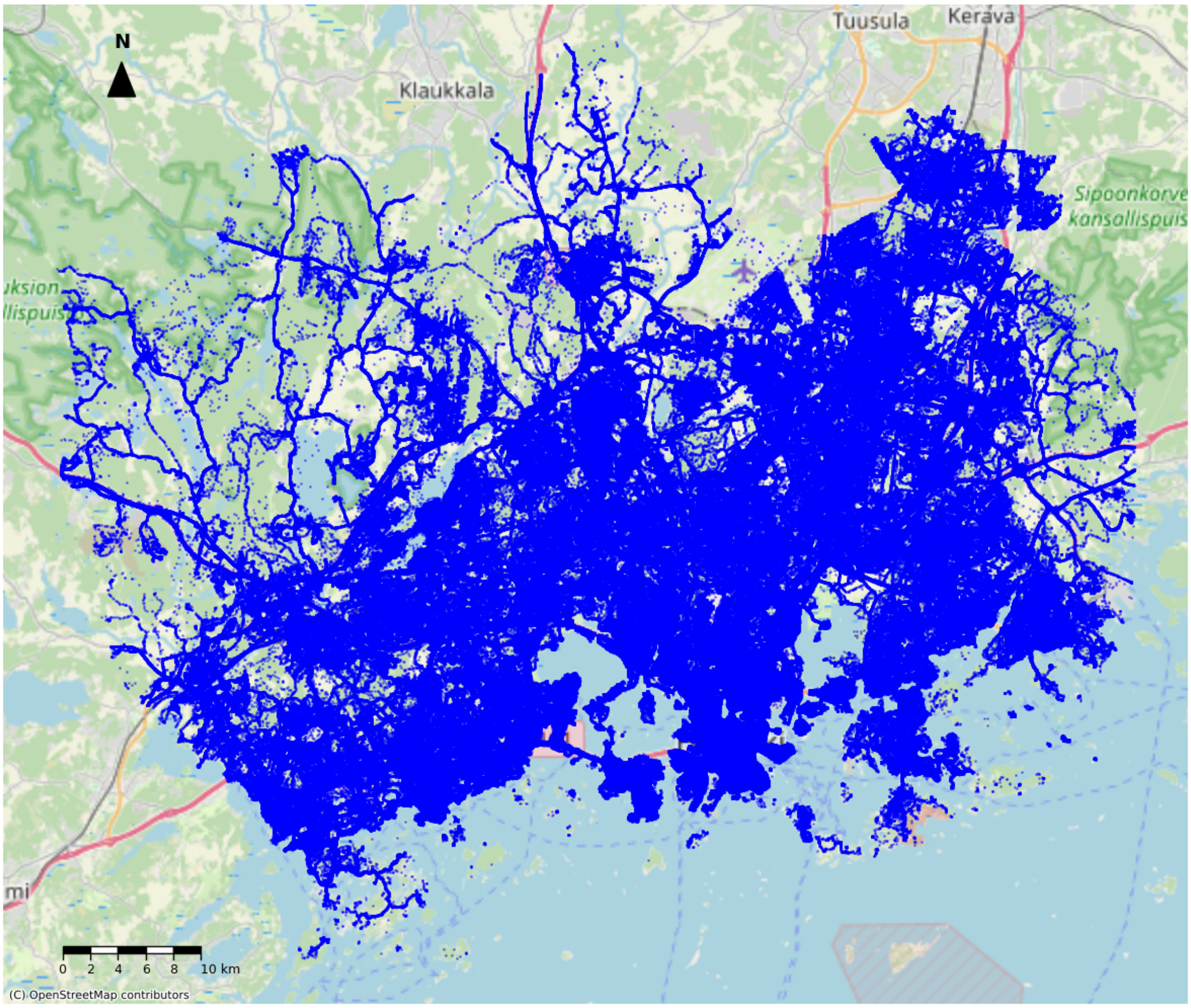

Figure 2: Raw Mobility Trajectories from the Locomizer Dataset Across the Helsinki Metropolitan Area.

Affinity profiles are calculated based on user interactions with public venues linked to specific activity types, within a defined geographical area. These interactions are categorised as positive, neutral (or zero), or negative. A positive interaction means the user is more likely than random chance to be present within the "interest area" of a venue during a specific time window, suggesting active engagement. A zero interaction indicates that the user has a random likelihood of presence, while a negative interaction means the user is less likely than random chance to be in that area at that time (Poliakov, 2018).

The scoring methodology is informed by Tobler's First Law of Geography, which states that closer things tend to be more related than distant ones (Tobler, 1970), and Huff's gravity model, which calculates the probability of spatial interaction based on distance and attractiveness (Huff, 1963). In this context, the closer a Point of Interest (POI) of a certain category is to the user, the higher the resulting affinity score. However, POI density also plays a significant role. In high-density areas, each individual POI exerts less unique influence due to the presence of similar alternatives, which reduces the per-POI affinity at the same distance. Nonetheless, when multiple POIs of the same type are located nearby, their combined influence results in a stronger overall pull toward that activity category. This approach is particularly effective for identifying disinterest, since users who consistently avoid dense clusters of POIs from a specific category are likely to have low affinity for that category (Poliakov, 2018).

To calculate the affinity score, Locomizer utilized the following formula:

$$A_{u,s,c} = \sum_i \ln \left(\frac{D_i \cdot B_{\max}^2}{G_c(B_i^2 - A_i^2)} \right)$$

For each signal-level Affinity Score $A_{u,s,c}$ representing the affinity of user u at signal s towards POI category c, the value reflects the cumulative affinity of all POIs belonging to category c within the relevant spatial sampling context. Specifically, each sampling group i is defined by a radial interval with minimum and maximum bounds A_i and B_i.The outermost radius across all intervals is denoted as $B_{\max}$ representing the extent of the neighbourhood area. Within each group i, D_i refers to the number of POIs belonging to category c, while G_c corresponds to the total number of POIs in that category across the entire neighbourhood (Poliakov, 2018).

Figure 3 below illustrates how a user's affinity score varies based on their distance from a Point of Interest (POI) and the surrounding density of POIs of the same type. The figure captures a single interaction signal from one user. In practice, multiple such signals are recorded over time and aggregated. For each user, the affinity score is calculated by summing and averaging these interaction signals across their historical movement patterns. In this study, the affinity profiles are computed on a monthly basis, with each profile representing a one-month window of observed user behaviour.

Distance from the user, meters	Number of POIs of the same type in the area																			
	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
25	5.99	5.30	4.89	4.61	4.38	4.20	4.05	3.91	3.79	3.69	3.59	3.51	3.43	3.35	3.28	3.22	3.16	3.10	3.05	3.00
50	4.89	4.20	3.79	3.51	3.28	3.10	2.95	2.81	2.70	2.59	2.49	2.41	2.33	2.25	2.18	2.12	2.06	2.00	1.95	1.90
75	4.38	3.69	3.28	3.00	2.77	2.59	2.44	2.30	2.18	2.08	1.98	1.90	1.82	1.74	1.67	1.61	1.55	1.49	1.44	1.39
100	4.05	3.35	2.95	2.66	2.44	2.25	2.10	1.97	1.85	1.74	1.65	1.56	1.48	1.41	1.34	1.27	1.21	1.16	1.10	1.05
125	3.79	3.10	2.70	2.41	2.18	2.00	1.85	1.71	1.60	1.49	1.40	1.31	1.23	1.16	1.09	1.02	0.96	0.90	0.85	0.80
150	3.59	2.90	2.49	2.21	1.98	1.80	1.65	1.51	1.40	1.29	1.20	1.11	1.03	0.95	0.89	0.82	0.76	0.70	0.65	0.60
175	3.43	2.73	2.33	2.04	1.82	1.63	1.48	1.35	1.23	1.12	1.03	0.94	0.86	0.79	0.72	0.65	0.59	0.54	0.48	0.43
200	3.28	2.59	2.18	1.90	1.67	1.49	1.34	1.20	1.09	0.98	0.89	0.80	0.72	0.64	0.58	0.51	0.45	0.39	0.34	0.29
225	3.16	2.47	2.06	1.77	1.55	1.37	1.21	1.08	0.96	0.86	0.76	0.67	0.59	0.52	0.45	0.39	0.33	0.27	0.21	0.16
250	3.05	2.35	1.95	1.66	1.44	1.26	1.10	0.97	0.85	0.74	0.65	0.56	0.48	0.41	0.34	0.27	0.21	0.16	0.10	0.05
275	2.95	2.25	1.85	1.56	1.34	1.16	1.00	0.87	0.75	0.64	0.55	0.46	0.38	0.31	0.24	0.17	0.11	0.06	0.00	-0.05
300	2.86	2.16	1.76	1.47	1.25	1.06	0.91	0.78	0.66	0.55	0.46	0.37	0.29	0.22	0.15	0.08	0.02	-0.03	-0.09	-0.14
325	2.77	2.08	1.67	1.39	1.16	0.98	0.83	0.69	0.58	0.47	0.37	0.29	0.21	0.13	0.06	0.00	-0.06	-0.12	-0.17	-0.22
350	2.70	2.00	1.60	1.31	1.09	0.90	0.75	0.62	0.50	0.39	0.30	0.21	0.13	0.06	-0.01	-0.08	-0.14	-0.19	-0.25	-0.30
375	2.62	1.93	1.53	1.24	1.01	0.83	0.68	0.54	0.43	0.32	0.23	0.14	0.06	-0.01	-0.08	-0.15	-0.21	-0.27	-0.32	-0.37
400	2.56	1.86	1.46	1.17	0.95	0.77	0.61	0.48	0.36	0.25	0.16	0.07	-0.01	-0.08	-0.15	-0.22	-0.28	-0.33	-0.39	-0.44
425	2.49	1.80	1.40	1.11	0.89	0.70	0.55	0.42	0.30	0.19	0.10	0.01	-0.07	-0.14	-0.21	-0.28	-0.34	-0.40	-0.45	-0.50
450	2.44	1.74	1.34	1.05	0.83	0.64	0.49	0.36	0.24	0.13	0.04	-0.05	-0.13	-0.20	-0.27	-0.34	-0.40	-0.45	-0.51	-0.56
475	2.38	1.69	1.28	0.99	0.77	0.59	0.43	0.30	0.18	0.08	-0.02	-0.10	-0.18	-0.26	-0.33	-0.39	-0.45	-0.51	-0.56	-0.62
500	2.33	1.63	1.23	0.94	0.72	0.54	0.38	0.25	0.13	0.03	-0.07	-0.16	-0.24	-0.31	-0.38	-0.44	-0.51	-0.56	-0.62	-0.67

Figure 3: Affinity Score Variation by Distance from POI and Local Density of Similar POIs.

3.2.2 Determining User's Home Location and List of Visitors

The identification of home locations is based on a parametric scoring system developed by Locomizer, which assigns temporal weights to user location signals depending on the time of day. All signals are first adjusted to the local time zone and spatially mapped to hexagonal grid cells. Each signal is then weighted according to the hour it was recorded. Signals captured between 00:00 and 01:59 are assigned a weight of 2.0, those between 02:00 and 03:59 receive a weight of 3.0, and those from 04:00 to 05:59 are again weighted at 2.0. Signals between 06:00 and 06:59, as well as those from 23:00 to 23:59, are given a weight of 1.0. For each user, the residential score of a hexagonal cell is calculated as the sum of all weighted signals occurring within that cell over the course of a month. The cell with the highest cumulative score is designated as the user's inferred home location (Locomizer, 2025). This approach is consistent with established practices for inferring residential locations from mobility data, as demonstrated in studies such as Dunning and Moore (2020) and Juhász et al. (2023).

Visitor classification is conducted using a rule-based algorithm guided by several parameters. A minimum gap of five consecutive days is required between visits, and only visits that occur within the 30-day window prior to the user's last recorded signal are considered. Additionally, a stay must not exceed five consecutive days to qualify as a visit. A user is classified as a visitor if they have made at least one such qualifying visit (Locomizer, 2025). This logic aligns with existing literature. For instance, Lin et al. (2023), in a study of visitor mobility in Jeju, observed that most visitors stayed for fewer than five days. They also found that nearly all visitors could be identified within a two-week observation period. These findings support the validity of the parameters used in this study.

3.2.3 Determining User's Economic Status

Median income is used as the primary indicator to distinguish between economically disadvantaged ("poor") and more affluent ("rich") neighbourhoods. In Finland, poverty is commonly assessed using a relative framework, in line with the at-risk-of-poverty (AROP) threshold. According to this framework, a household is considered at risk of poverty if its annual disposable income falls below 60 percent of the national median (Järvinen and Saarinen, 2021).

Based on supplementary data from Statistics Finland (2024) and shapefile from Helsinki Region Infoshare (2023), this threshold corresponds to an annual disposable household income of €30,000. This figure is used to classify users according to the income level of their inferred home location. Specifically, if a user's predicted home falls within an area where the median household income is below €30,000, they are labelled as "Below Median Income". Conversely, users residing in areas with median incomes above this threshold are classified as "Above Median Income", as shown in Figure 4. It is important to acknowledge the limitations of this area-based classification. Relying on neighbourhood-level median income can introduce ecological fallacies, as not all individuals in lower-income areas are necessarily poor, and not all individuals in higher-income areas are affluent. Nonetheless, this approach offers a practical and widely accepted method for incorporating socio-economic context into mobility analysis.

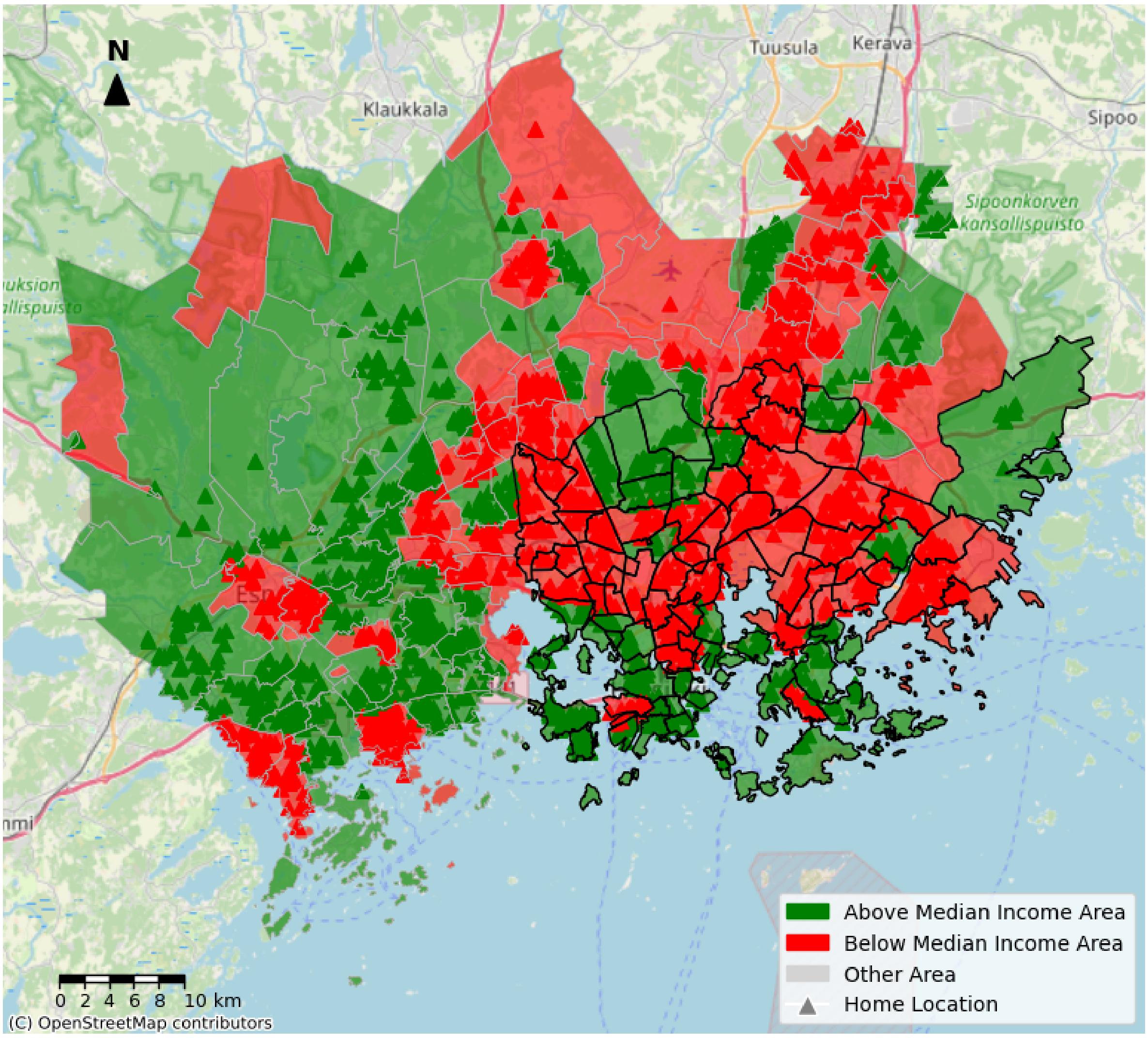

Figure 4: Spatial Distribution of Residential Areas by Median Income in Helsinki.

3.3 Data-Preprocessing

3.3.1 Filter out Data

The Locomizer Helsinki Dataset (July–September 2024) contains 398,322,023 GPS points from 643,503 unique users. To ensure the analysis focuses on consistent and meaningful mobility patterns, the dataset was filtered to include only users with at least 20 distinct days of recorded mobility data in each of the three months. Additionally, user IDs flagged as short-term visitors by Locomizer were excluded in order to maintain analytical emphasis on long-term local behaviour. This filtering approach aligns with practices in previous mobility studies, where short-term or noisy traces are often removed to improve data reliability (Wang et al., 2021; Wang et al., 2025; Liao et al., 2025). To further enhance data quality, an interquartile range (IQR) filter was applied to the latitude and longitude values. This helps to remove spatial outliers caused by GPS noise or erroneous signals (Law et al., 2025). The analysis was then geographically restricted to GPS points located within a 10-kilometre radius of the Helsinki city centre. This distance threshold was selected based on the high concentration of urban activity in central areas and is consistent with the spatial scope used in other research (Kang, 2025).

Once the final user list was determined, each user was assigned a dominant amenity category based on their affinity scores. For each category, the median affinity score was calculated across all users. A user was considered to have a meaningful interest in a given category if their individual score exceeded the median. Among the categories where the user's score was above the median, the one with the highest value was selected as their dominant affinity profile for that month. If the user did not exceed the median in any category, they were classified as having a mixed profile. For modelling purposes, the profile category used was the user's dominant affinity profile from the previous month, rather than the current one. This decision was made to preserve temporal consistency and prevent data leakage. Using the previous month's data ensures that the model only relies on information that would have been available at the time of prediction.

3.3.2 Calculating per-User Exposure for Experienced Segregation Analysis

One of the essential parts of this analysis is to quantify how often users come into close physical proximity with others who differ from them in terms of economic status or behavioural affinity. The underlying assumption is that individuals may consciously or unconsciously choose to visit places where they are more likely to encounter others who are either socially similar or different from themselves.

The methodological foundation for this analysis is based on the work of Nilforoshan et al. (2023), who introduced a high-resolution framework for measuring experienced segregation in urban environments. Their approach builds on the "cosmopolitan mixing hypothesis," which posits that cities, through a combination of high population density, spatial constraints, and accessible public transport, tend to increase the likelihood of interaction between diverse individuals. To operationalise this concept, Nilforoshan et al. (2023) define an exposure event as an instance where two individuals are located within 50 metres of each other during a five-minute time window. These thresholds are designed to capture visual or ambient exposure and are supported by previous research suggesting that even brief encounters with socially dissimilar individuals can have lasting effects.

Figure 5: Path-Crossing Event Illustration (Inspired by Nilforoshan et al., 2023).

Following the same parameters, this study detects exposure events by evaluating, for each user and timestamp, three key metrics: (1) the number of nearby users from a different economic group, (2) the number of users with a different dominant behavioural affinity based on the previous month, and (3) the total number of co-located users within 50 metres during a five-minute period.

Given the sparsity and uneven distribution of GPS-based mobility data, it is expected that many time windows will contain few or no interaction events. To address this, Laplace smoothing is applied to the contact rate variables. This technique helps stabilise the values, particularly in cases with low or zero contact counts, thereby improving robustness and interpretability in an analysis, including those that focus on fairness and exposure inequality (Boodidhi, 2011; Daniel and Martin, 2025). A binary variable is also created to indicate whether any interaction occurred. In addition, a capped log-transformed variable is used to reduce skewness and minimise the influence of outliers (Jeong, Leconte and Proutiere, 2016; Nahhas, 2025; Reifman and Keyton, 2012).

3.4 Schelling-Inspired Simulation of Socio-Spatial Avoidance Logic

After the final dataset was cleaned and prepared, the next step involved visualising road network usage by users, segmented by income group. This analysis compares users from above-median and below-median income categories. The user trajectories represent realistic travel routes across Helsinki, generated using shortest-path calculations over the road network. Each route was analysed by identifying the road segments it intersects. For every segment traversed by a user, a counter was incremented based on the user's income classification. These counts were then aggregated across all users to determine the dominant economic group associated with each road segment.

Segments where more than 70 percent of users belonged to the above-median income group were classified as Above-Median Dominant and visualised in green. Segments where fewer than 30 percent of users came from the above-median group, or where most users were from the below-median group, were labelled Below-Median Dominant and visualised in red. Segments with a more balanced usage pattern were classified as Mixed roads and displayed in blue. Any segment not traversed by users during the observation period was shown in light grey. This classification formed the foundation for the Schelling-inspired simulation in the next stage of analysis.

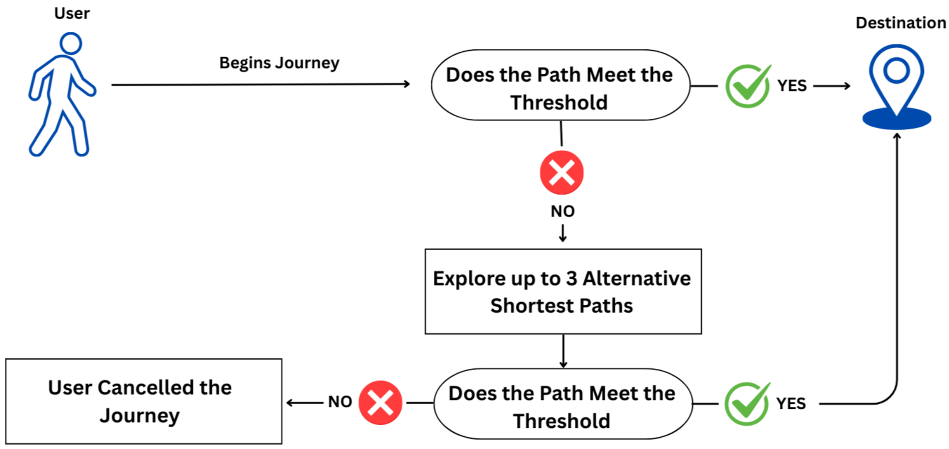

Figure 6: Flowchart of Schelling-Inspired Mobility Simulation.

The core of the simulation involves a threshold-based routing process. Users are modelled as agents who selectively avoid road segments predominantly used by the opposite income group, based on their level of tolerance. Each agent is assigned a tolerance threshold that defines the maximum acceptable share of road usage by the opposite group. Threshold values range from 1.0, representing complete tolerance, to 0.1, representing very low tolerance, thereby simulating different degrees of socio-spatial avoidance.

For each threshold level, the simulation proceeds through a series of steps. First, the user's original route is assessed. If all segments along the route fall within the tolerance threshold, the path is accepted and marked as used. If any segment exceeds the tolerance limit, the system attempts to calculate at maximum three new shortest paths, based on Dijkstra's (1959) algorithm, between the same start and end points that avoids high-exposure segments. If a valid path cannot be found under these constraints, a fallback mechanism is activated. The system performs a constrained breadth-first search to explore up to three simple alternative paths. This step reflects realistic re-routing attempts that a user might make. If no valid path is found after these steps, the trip is marked as failed, and the agent is considered to have cancelled travel due to excessive exposure to dissimilar users.

3.5 Next Location Model Architectures

3.5.1 Splitting the Dataset

The dataset is split according to an inductive learning setting. This approach is designed to simulate a real-world scenario in which a model must predict future locations that were not observed during training. In the context of next-location prediction using human mobility data from Helsinki, the inductive setting ensures that the model is evaluated on its ability to generalise to previously unseen Points of Interest (POIs). This reflects practical use cases, such as urban environments where new POIs are continuously emerging. The methodology follows the framework by Wang et al. (2025), who advocate for inductive learning as a more realistic and rigorous benchmark for mobility prediction tasks.

Figure 7: Inductive Split Logic.

The dataset is divided into training and testing sets based on temporal order, which is a common practice in next-location prediction tasks (Feng et al., 2018). Mobility records from July and August are used for training, while records from September are reserved for testing. To increase the inductive challenge, 10 percent of the Points of Interest (POIs) present in the training data are randomly selected and excluded from the training set, although they are retained in the test set. This setup simulates real-world scenarios in which models must predict visits to newly emerging or previously unseen POIs, thereby assessing the model's ability to generalise beyond its training experience.

3.5.2 Model Architectures

The models used in this study represent a range of recurrent neural network (RNN) architectures tailored for next-location prediction. GRU4Rec models each session as a sequence of events, where the item in the current timestep is represented by a one-hot vector. This vector is passed as input to the network, which then outputs a set of scores corresponding to the likelihood of each item being the next in the session. The model is trained by iterating through all events in the sequence, updating its parameters to better predict subsequent locations (Hidasi and Karatzoglou, 2018). ST-RNN (Spatial Temporal Recurrent Neural Networks) extends the standard RNN by incorporating spatial and temporal dependencies. It introduces time-specific and location-specific transition matrices, allowing the model to learn how spatial and temporal gaps influence movement patterns. Each layer in the network learns upper and lower bounds for these matrices, and the final transition values are computed through linear interpolation, which enables the model to adapt flexibly to varying intervals between events (Liu et al., 2016; Luca et al., 2021).

DeepMove is an attentional recurrent model designed to handle long and sparse mobility trajectories. The architecture begins by embedding both historical and current trajectory information into a dense representation that captures spatio-temporal and user-specific features. Historical trajectories are processed using an attention mechanism, which extracts salient mobility patterns. In parallel, a GRU encodes the current trajectory. The outputs of the attention layer, GRU, and multi-modal embedding module are then concatenated and passed through a fully connected layer to predict the next location (Feng et al., 2018; Luca et al., 2021). At the core of this study is a comparative analysis between the baseline performance of each model and its modified counterpart, in which the author incorporates segregation-related metrics into the model architecture.

The original architecture of each model is preserved, and segregation metrics are introduced as an additional seven-dimensional feature vector. These metrics are integrated into the models as contextual signals without modifying their core learning mechanisms. For GRU4Rec, the segregation vector is projected and added to the item embeddings at each timestep, before being passed into the GRU layer. For ST-RNN, the projected segregation vector is added to the hidden state before the classification step. This allows the model to incorporate socio-spatial context while keeping the spatio-temporal transition dynamics intact. In the case of DeepMove, the segregation vector is projected and concatenated with the short-term GRU output, the long-term attention-based context, and the user embedding to form the final representation before prediction.

This approach is consistent with established practices in the literature, where contextual features are either incorporated into the input of the recurrent layer or connected to the output layer to enrich the model's representational capacity (Hoang, Haffari and Cohn, 2016; Smirnova and Vasile, 2017). All models, including both the baseline and the versions enhanced with segregation metrics, are trained on the same dataset using an identical preprocessing pipeline. This ensures a fair comparison and isolates the effect of the added socio-spatial features. Figures 8-10 showcased the details about the modifications of the model architectures.

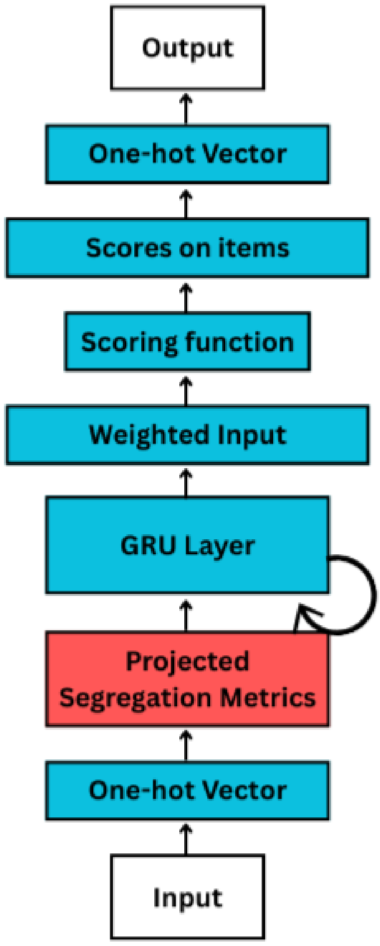

Figure 8: Modified GRU4Rec Architecture.

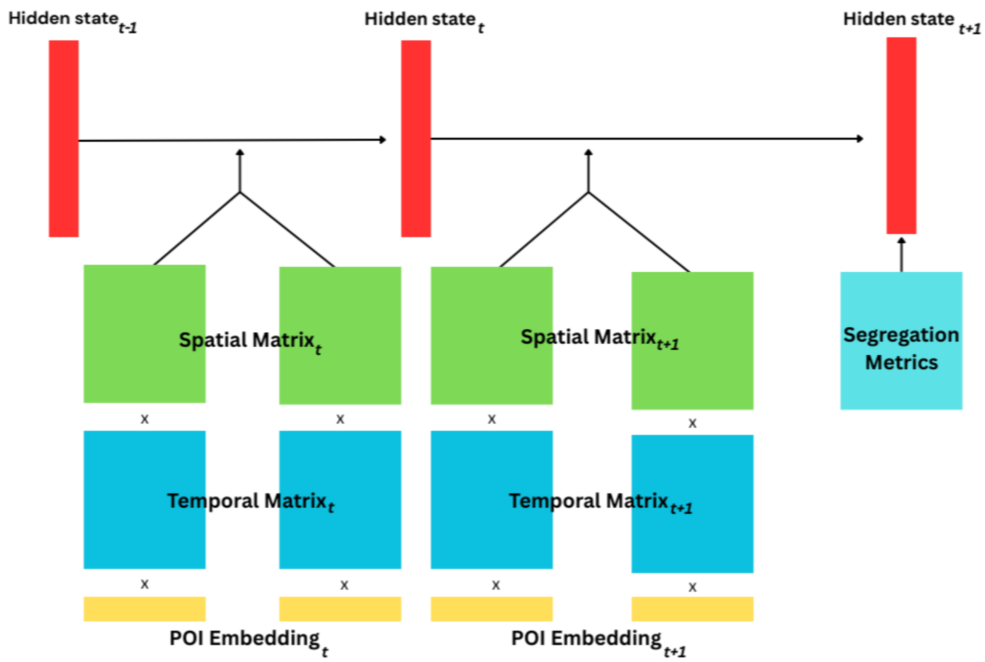

Figure 9: Modified ST-RNN Architecture.

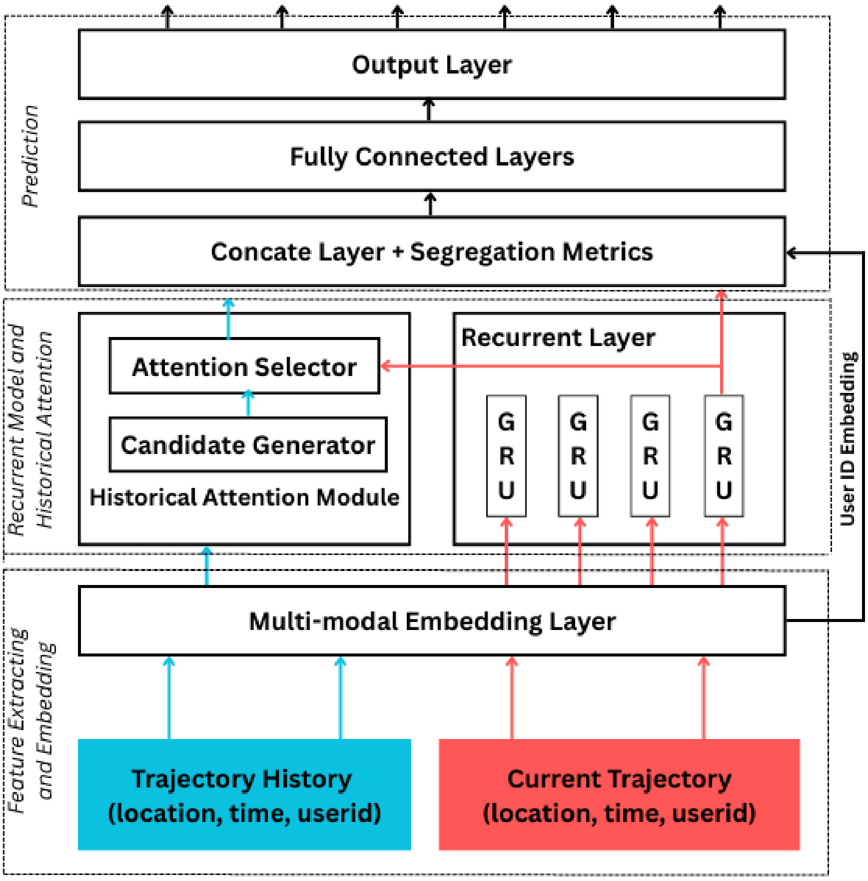

Figure 10: Modified DeepMove Architecture.

3.5.3 Model Parameters and Evaluation

All model parameters were selected based on the official GitHub repositories for each architecture, with an effort to keep them as consistent and comparable as possible. Model training and evaluation were conducted using Google Colab to take advantage of GPU acceleration. Specifically, the A100 GPU available in Colab was used for training. Despite this, computational limitations were encountered due to the large size of the dataset.

To address memory constraints within the Colab environment, different batch sizes were selected for each model during the hyperparameter tuning process. Although batch size can influence convergence behaviour, the primary consideration in this context was to maintain training stability and avoid memory overflow on both GPU and CPU. All other training parameters, including the number of epochs, learning rate, and choice of optimiser, were kept as consistent as possible across experiments to ensure a fair basis for comparison.

Table 1: Training Configuration for Each Model.

Model	Optimizer	Learning Rate	Batch Size	Epochs	Loss Function
GRU4Rec	Adam	0.001	4	10	Sampled Softmax + CrossEntropy
ST-RNN	Adam	0.001	64	10	CrossEntropy
DeepMove	Adam	0.001	128	10	Negative Log Likelihood

For DeepMove, the original authors employed negative sampling as a training strategy to approximate the log probability of the softmax function. This technique significantly accelerates convergence by reducing the computational complexity of calculating the full softmax, making it particularly effective for large-scale location prediction tasks (Feng et al., 2018). This study specifically employed the Attention Average Long User variant of the DeepMove model, as it demonstrated strong predictive performance in the original evaluation by Feng et al. (2018). In the case of GRU4Rec, the model uses a cross-entropy loss function. While cross-entropy is inherently a pointwise loss, combining it with the softmax operation introduces listwise characteristics. This is because the softmax normalisation couples the output scores, meaning the loss cannot be decomposed into independent terms. This listwise property has been shown to improve ranking quality in sequential recommendation tasks (Hidasi and Karatzoglou, 2018).

To evaluate the predictive performance of the models, the author used Acc@k, MRR, and nDCG@k. The primary metric is Top-k Accuracy (Acc@k), where model predictions are sorted in descending order by their estimated probability of being the next location. Acc@k measures the proportion of test instances in which the true next location appears within the top k predicted candidates (Wang et al., 2025).

Another evaluation metric is the Mean Reciprocal Rank (MRR), which captures how highly the correct answer is ranked within the predicted list. For each test case, the reciprocal rank is calculated as 1 divided by the position of the correct location in the ranked list. For instance, if the correct location is ranked first, the reciprocal rank is 1; if ranked second, it is 0.5, and so on. The MRR is then computed as the average reciprocal rank across all test samples. This measure is more stringent than accuracy-based metrics, as it accounts not only for whether the correct location is present in the top-k list, but also for how early it appears (Nezhadettehad et al., 2025; Wang et al., 2025). Formally, if N is the number of test samples and rank_i is the rank of the ground-truth location for the i-th test case, then:

$$\text{MRR} = \frac{1}{N} \sum_{i=1}^{N} \frac{1}{\text{rank}_i}$$

The Normalised Discounted Cumulative Gain (nDCG) at rank position k evaluates the quality of a ranked prediction list by comparing the actual ordering (DCG) to the ideal ordering (IDCG). The calculation of nDCG@k is given below:

$$\text{nDCG@}k = \frac{\text{DCG}_k}{\text{IDCG}_k},$$

$$\text{DCG}_k = \sum_{j=1}^{k} \frac{r_j}{\log_2(j+1)},$$

where r_j denotes the relevance score at rank position j. In the context of next-location prediction, relevance is binary like $r_j \in \{0, 1\}$ with $r_j = 1$ if and only if the j-th predicted location matches the actual next location in the ground truth, based on the ranked probabilities $P(\hat{l}_{n+1})$ (Wang et al., 2025).

4 Results

4.1 Exploratory Data Analysis

The original dataset comprises 398,322,023 GPS points collected from 643,503 unique users. To ensure consistent user activity, the dataset was filtered to retain only those users who recorded mobility data on at least 20 distinct days per month. From this filtered group, only users whose trajectories were predominantly located within the Helsinki metropolitan area were selected for further analysis. Following this filtering process, an inductive split was applied to separate the users into training and testing sets. The final training set includes 2,855 users and a total of 3,085,993 GPS points, while the test set consists of 2,752 users with 1,624,759 GPS points.

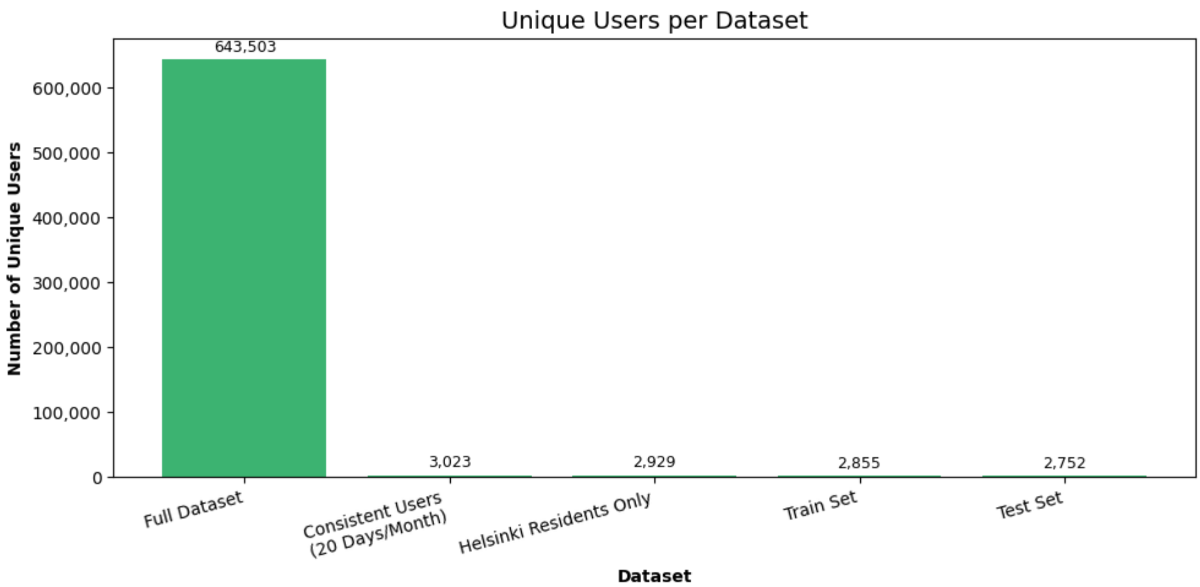

Figure 11: Comparison of Datasets (Unique Users).

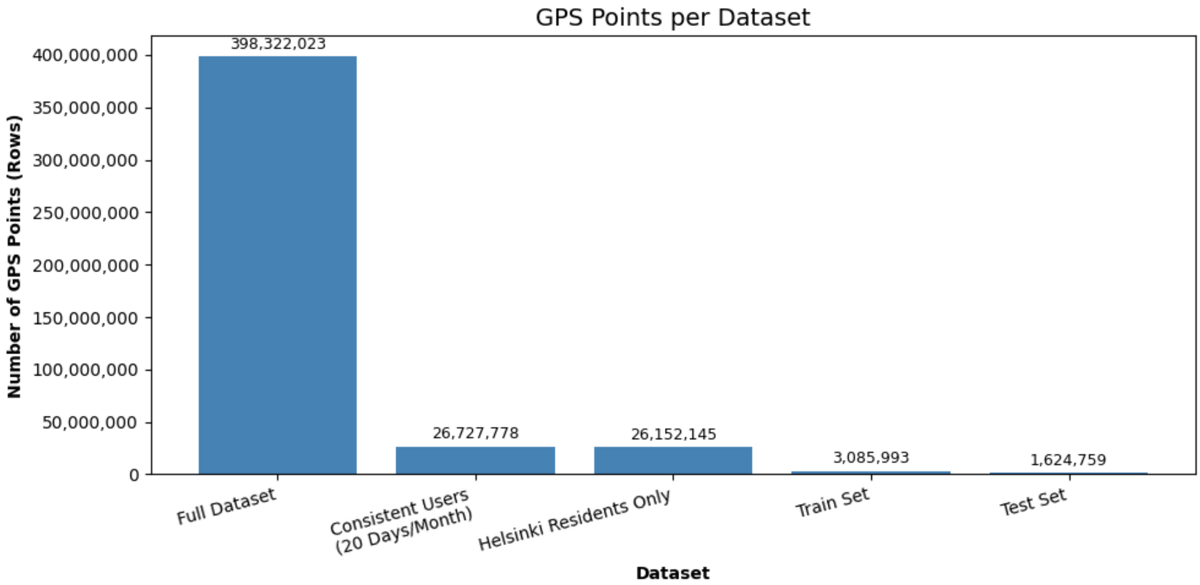

Figure 12: Comparison of Datasets (GPS Points).

Figure 13 presents the distribution of economic categories among users in the training and testing datasets, broken down by month. In both training months, users classified as Below Median Income consistently outnumber those from the Above Median Income group. This pattern remains consistent in the testing set, where the number of users from the Below Median Income group continues to exceed that of their higher-income counterparts.

Figure 14 shows the distribution of the top 10 affinity profiles across the same temporal split. Throughout all three months, "Automotive Repair Services and Parking" emerged as the most dominant category, suggesting a strong and stable interest in mobility-related infrastructure. Other consistently high-ranking categories include "Sports", "Educational Services", and "Amusement and Recreation Services", indicating sustained engagement with recreational and institutional activities.

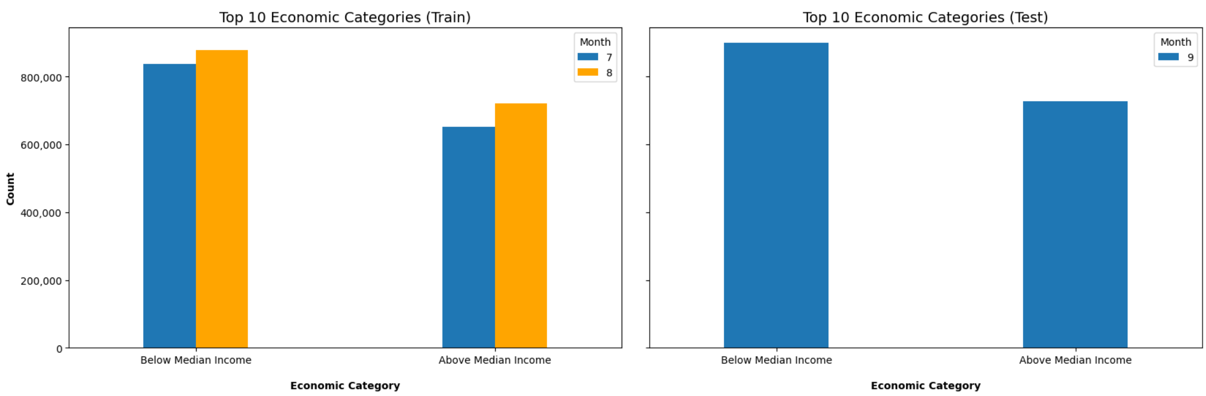

Figure 13: Distribution of Economic Categories in the Datasets.

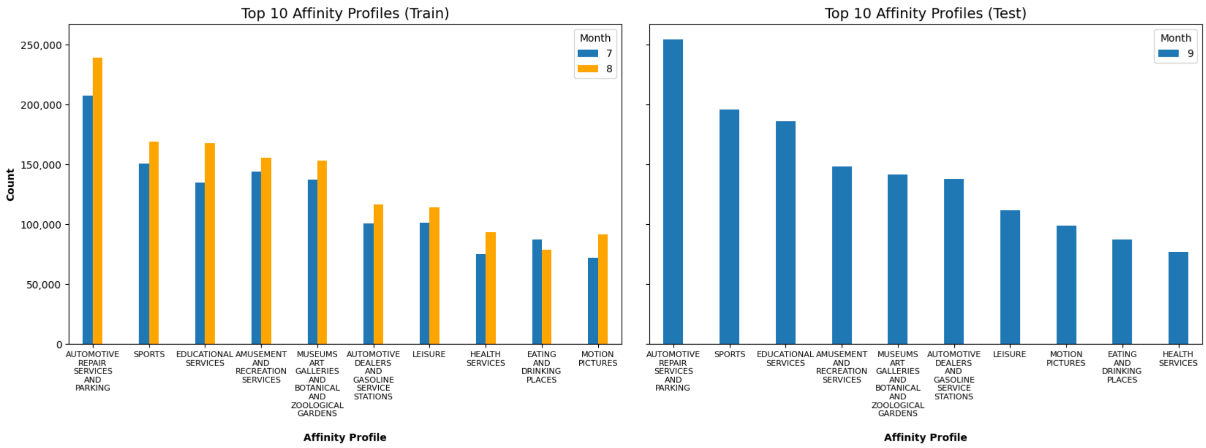

Figure 14: Distribution of Affinity Profiles in the Datasets.

Figure 15 illustrates the distribution of total contact events in both the training and testing datasets. It is evident that the majority of observations contain zero recorded contacts. Specifically, only 8.89% of records in the training set and 8.24% in the test set involve more than zero contact events. This high proportion of zero-contact instances highlights the sparsity of interaction data, which poses challenges for downstream analysis. These results further justify the application of smoothing techniques to stabilise the data and ensure that models trained on these features remain robust and interpretable.

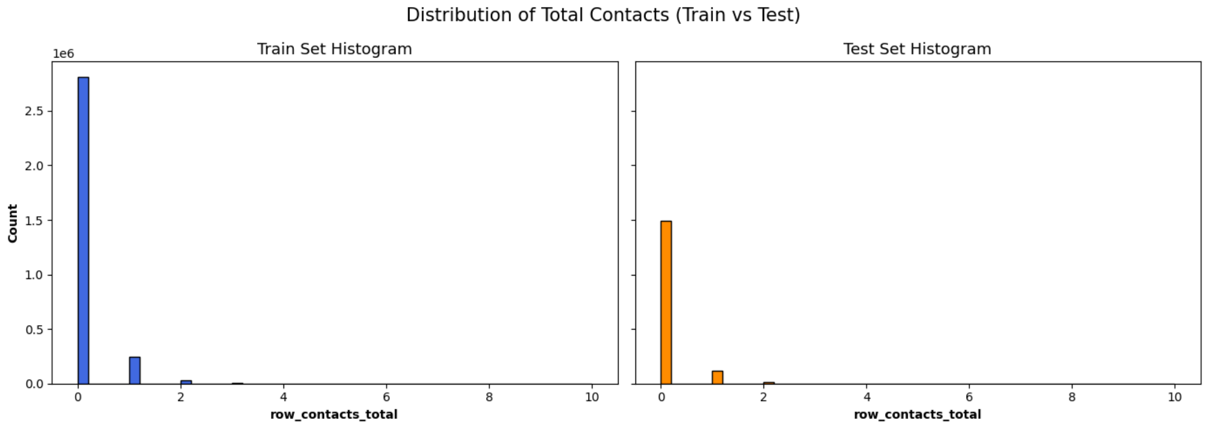

Figure 15: Distribution of Total Row-Level Contacts.

4.2 Road Usage and Schelling-Inspired Mobility Simulation

In terms of road usage within the Helsinki city centre, the resulting visualisation reveals that a large proportion of roads are classified as mixed, indicating shared use by both income groups. However, distinct clusters of roads are also visible, showing predominant use by either above-median or below-median income users. Notably, roads in the southwest of the city tend to be dominated by above-median income users, while roads in the northeast are more frequently used by users from the below-median income group. These spatial patterns closely reflect the economic classification of surrounding neighbourhoods, suggesting that income-based residential segregation may also shape daily mobility behaviour and access to infrastructure.

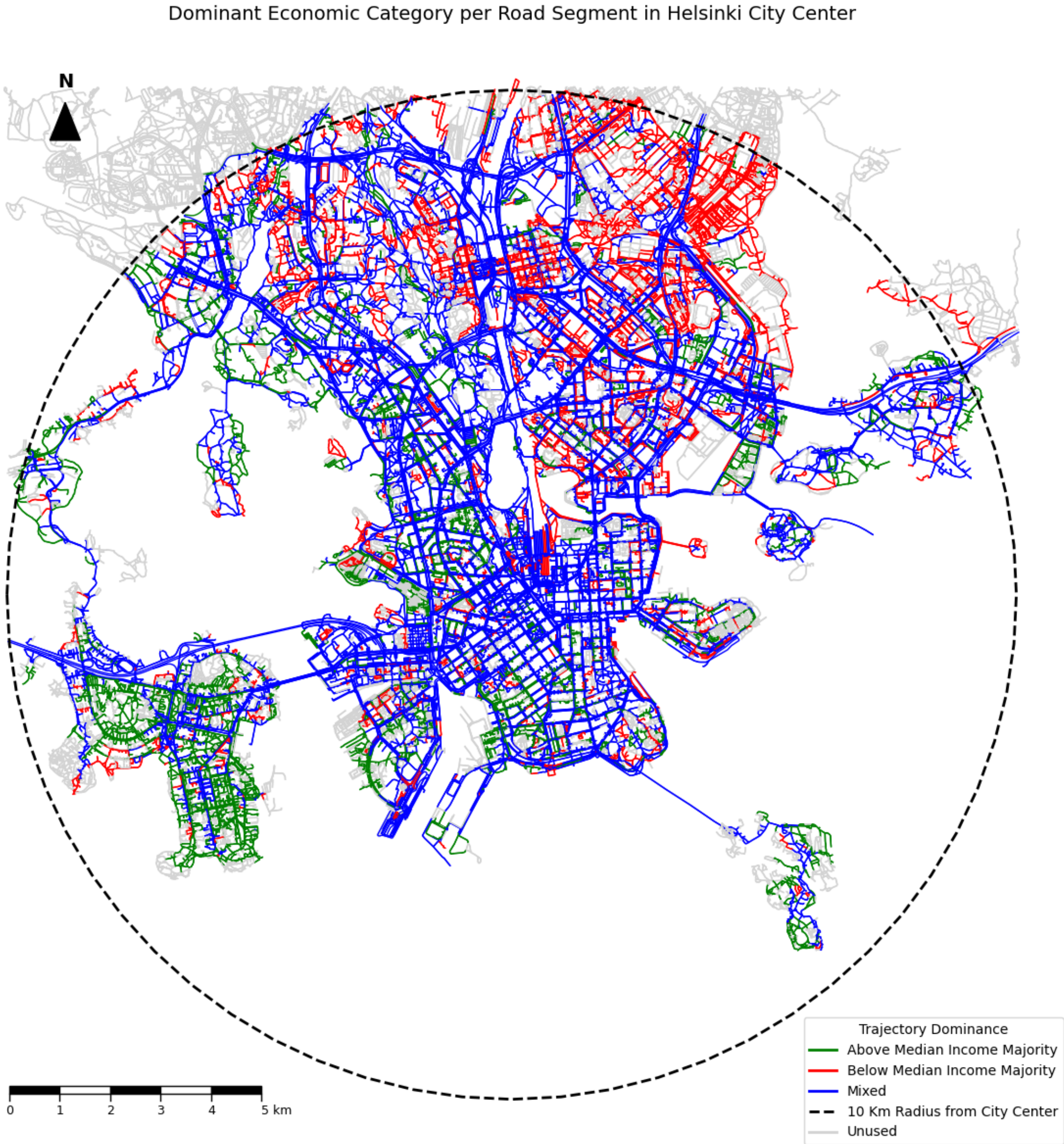

Figure 16: Dominant Economic Group per Road Segment in Central Helsinki.

To gain deeper insights into the spatial structure of socio-economic segregation, the analysis was further disaggregated by affinity profile. This visual breakdown enables a more nuanced understanding of how segregation patterns vary across different types of user interests. A key finding is that the degree of spatial segregation in mobility is not consistent across all categories, but instead varies considerably depending on the activity type.

For example, categories such as "Leisure" and "Apparel and Accessory Stores" exhibit noticeable clustering of red road segments, particularly in the northern and eastern parts of Helsinki. This pattern suggests that below-median income users are more likely to travel through or engage in activities within these areas. In contrast, categories like "Shopping" and "Mixed" display broader geographic dispersion. In these cases, green segments, which represent above-median income users, appear more frequently in the city centre and southern parts of the region.

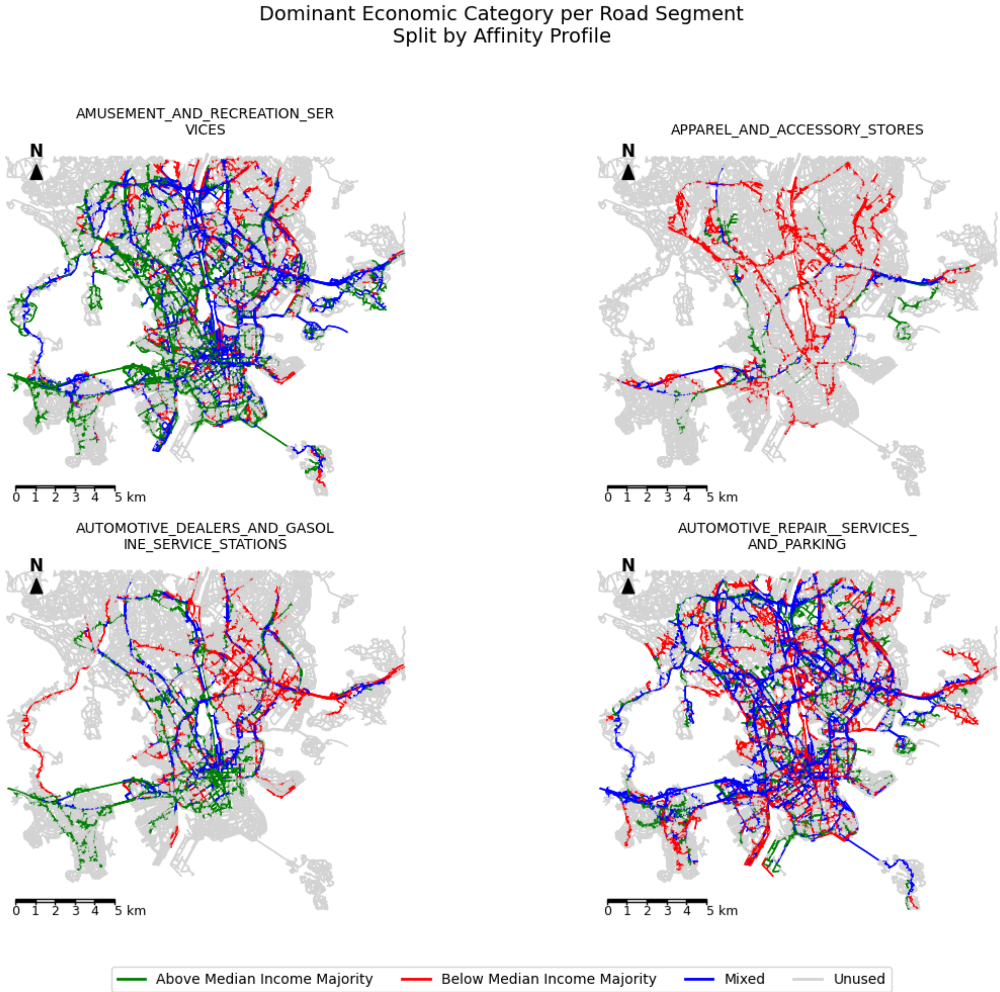

Figure 17: Dominant Economic Group per Road Segment by Affinity Profile (Part 1).

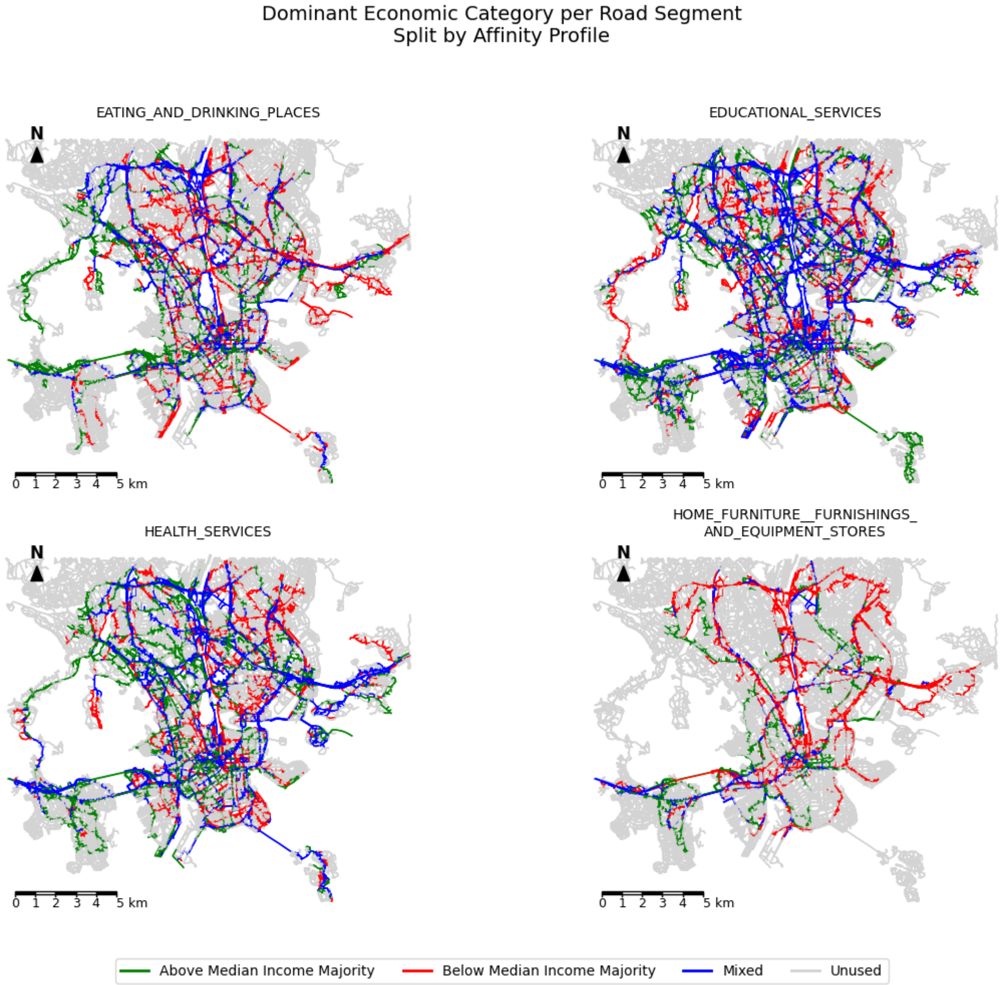

Figure 18: Dominant Economic Group per Road Segment by Affinity Profile (Part 2).

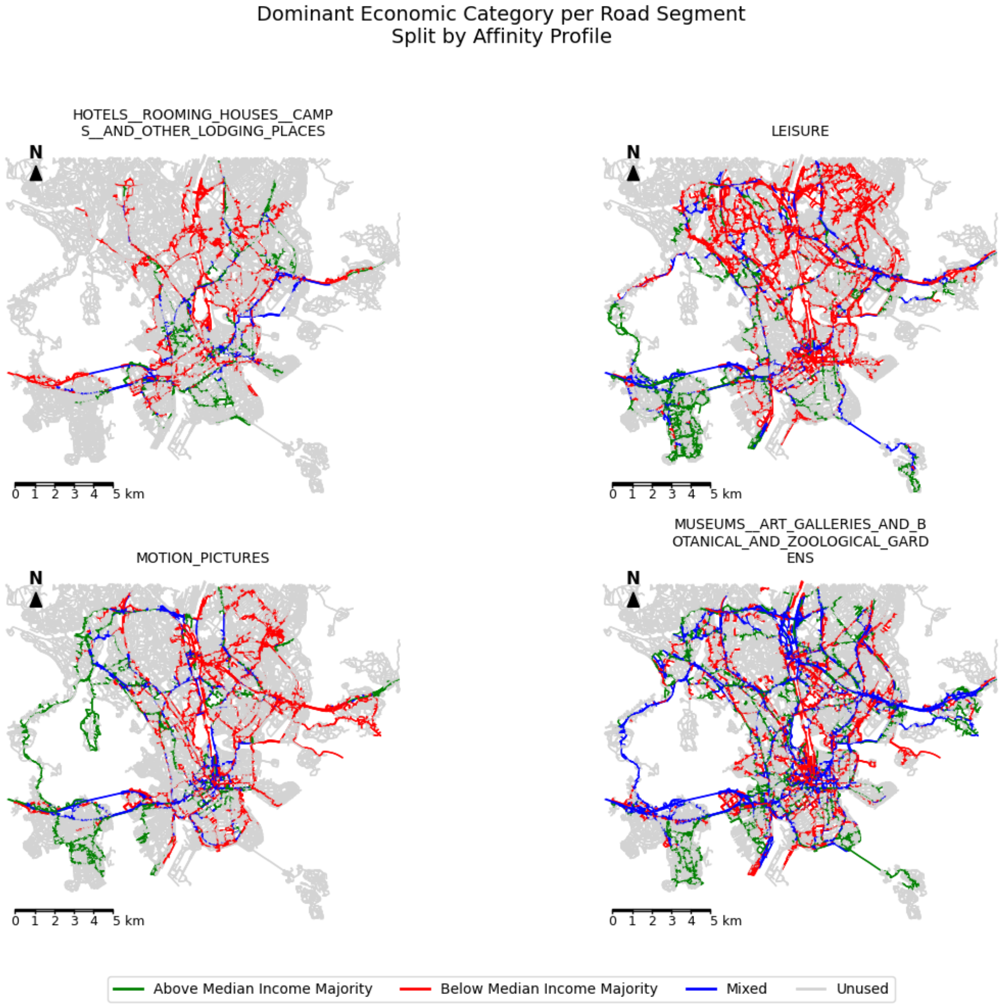

Figure 19: Dominant Economic Group per Road Segment by Affinity Profile (Part 3).

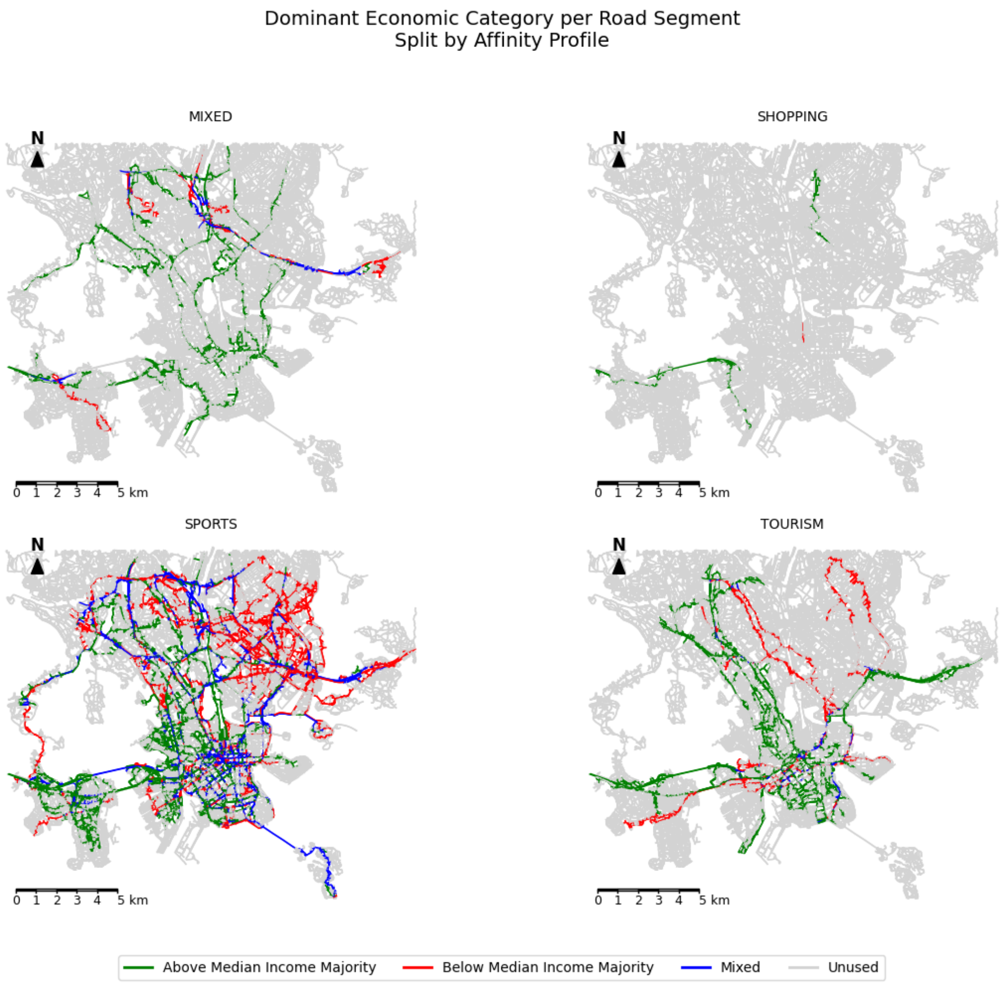

Figure 20: Dominant Economic Group per Road Segment by Affinity Profile (Part 4).

Some affinity profiles demonstrate higher levels of integration in terms of road usage across income groups. For instance, categories such as "Educational Services" and "Automotive Repair Services and Parking" show a broad spatial distribution of green, red, and blue road segments. This pattern indicates that the infrastructure related to these activities is more evenly accessed and utilised by both above-median and below-median income users. Across most affinity categories, the city centre consistently emerges as a zone of integration. This is evidenced by the high concentration of blue segments, which reflect shared road usage between the two income groups.

In the context of the Schelling-inspired simulation, the level of tolerance assigned to agents plays a critical role in shaping mobility patterns. Higher threshold values, which indicate greater tolerance toward dissimilar users, result in a greater presence of mixed (blue) roads. However, the number of mixed roads drops significantly once the threshold is reduced to 0.7. At a threshold of 0.6, distinct clusters emerge, revealing spatial separation between roads primarily used by either above- or below-median income users.

When the threshold is further reduced to 0.5, the number of coloured road segments declines dramatically. This reflects an increase in cancelled trips, as agents are more likely to abandon travel when encountering routes with excessive exposure to the opposite group. From a threshold of 0.4 and below, grey roads, which represent unused or inaccessible segments, begin to dominate the map.

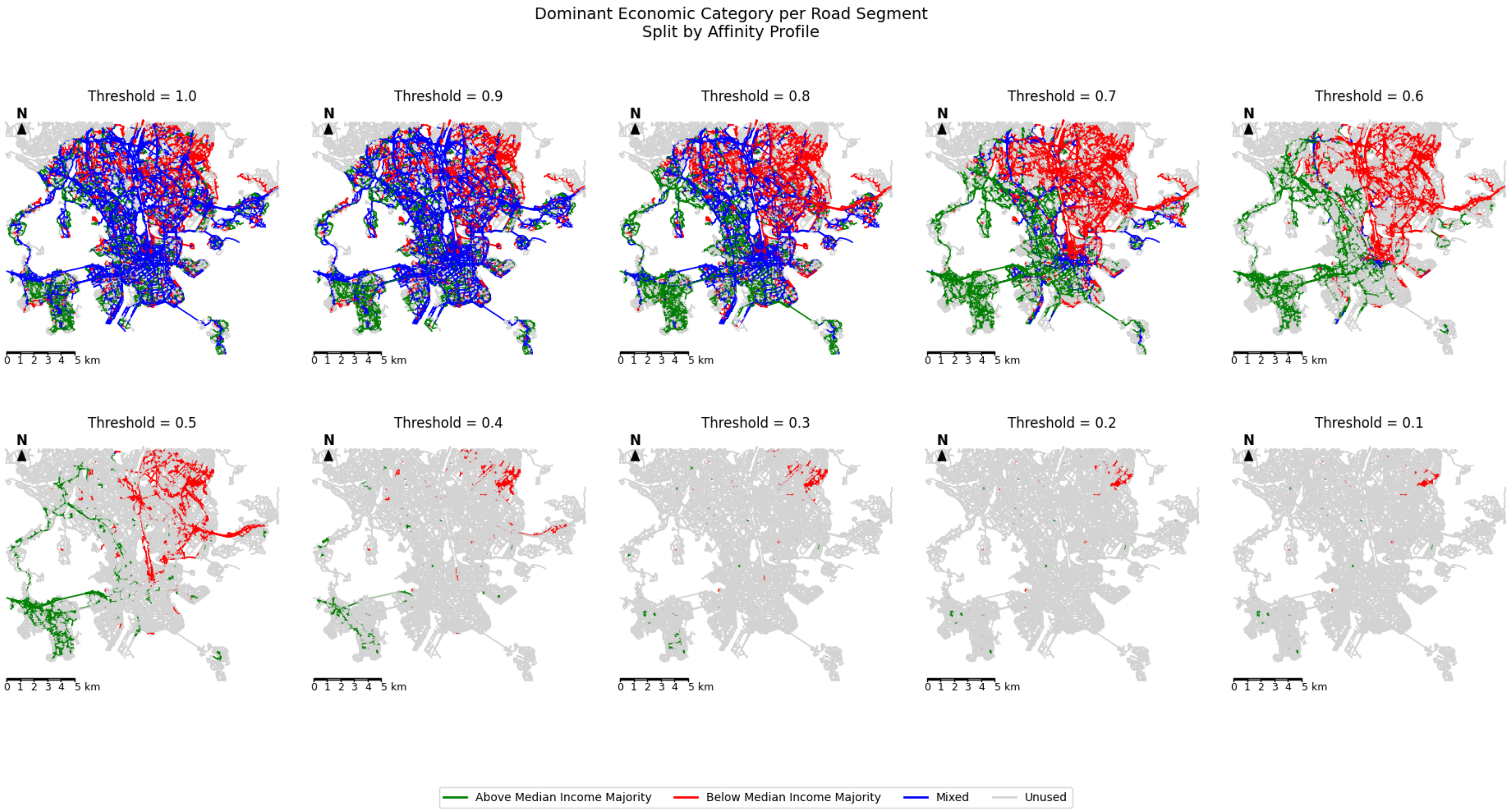

Figure 21: Schelling-Inspired Mobility Simulation.

4.3 Next Location Prediction Result

When comparing next-location prediction models, both the baseline versions and those enhanced with segregation metrics were evaluated across multiple performance measures. Among all models, the best-performing configuration was the DeepMove (Attention Average Long User) model with the addition of segregation metrics, achieving a Top-1 Accuracy (Acc@1) of 56.52%. This represents a marginal improvement over the baseline DeepMove model, which achieved 56.49%, reflecting a gain of approximately 0.06 percentage points. Further details can be seen at Table 2 where the bold values indicate the best performance for each metric, while the underlined values represent the second-best performance.

Across the other evaluation metrics, the baseline and modified DeepMove models continued to outperform the other architectures. The baseline version performed slightly better in terms of Acc@5, Acc@10, and Mean Reciprocal Rank (MRR). In contrast, the segregation-enhanced version showed a minor improvement in nDCG@10, with an increase of 0.02 percentage points.

Table 2: Performance Comparison of Next-Location Prediction Models With and Without Segregation Metrics.

Logic	**Model**	**Inductive Split (Time-Based Split)**				
		Acc@1	**Acc@5**	**Acc@10**	**MRR**	**nDCG @10**
Baseline Model	GRU4Rec	37.56	41.89	42.57	40.30	39.55
	ST-RNN	50.81	62.92	67.34	58.87	56.19
	DeepMove (Attn. Avg. Long User)	<u>56.49</u>	**71.49**	**77.32**	**66.48**	<u>63.07</u>
Baseline Model + Segregation Metrics	GRU4Rec	37.59	42.30	43.42	40.63	39.73
	ST-RNN	50.81	62.84	67.15	58.80	56.15
	DeepMove (Attn. Avg. Long User)	**56.52**	<u>71.47</u>	<u>77.19</u>	<u>66.46</u>	**63.08**
Rel.Diff %		**0.06%**	**-0.03%**	**-0.16%**	**-0.03%**	**0.02%**

When comparing the original baseline models to their modified counterparts, GRU4Rec showed the greatest performance improvement following the integration of segregation-related variables. The modified version achieved increases of 0.08% in Acc@1, 0.97% in Acc@5, 2.01% in Acc@10, 0.83% in MRR, and 0.46% in nDCG@10. These gains are notable, particularly when considering that some journal articles have proposed entirely new model architectures for next-location prediction and reported comparable performance improvements over more established baselines (Wang et al., 2025). By contrast, the ST-RNN model exhibited the weakest response to the inclusion of segregation variables. While it showed a marginal improvement of 0.01% in Acc@1, performance declined across the other evaluation metrics. These results, summarised in Table 3 and Figure 22.

Table 3: Relative Performance Difference of Segregation-Based in comparison to the Baseline Models.

Model	Inductive Split (Time Based Split)				
	Acc@1	**Acc@5**	**Acc@10**	**MRR**	**nDCG@10**
GRU4Rec	0.08%	0.97%	2.01%	0.83%	0.46%
ST-RNN	0.01%	-0.14%	-0.28%	-0.12%	-0.07%
DeepMove (Attention Average Long User)	0.06%	-0.03%	-0.16%	-0.03%	0.02%

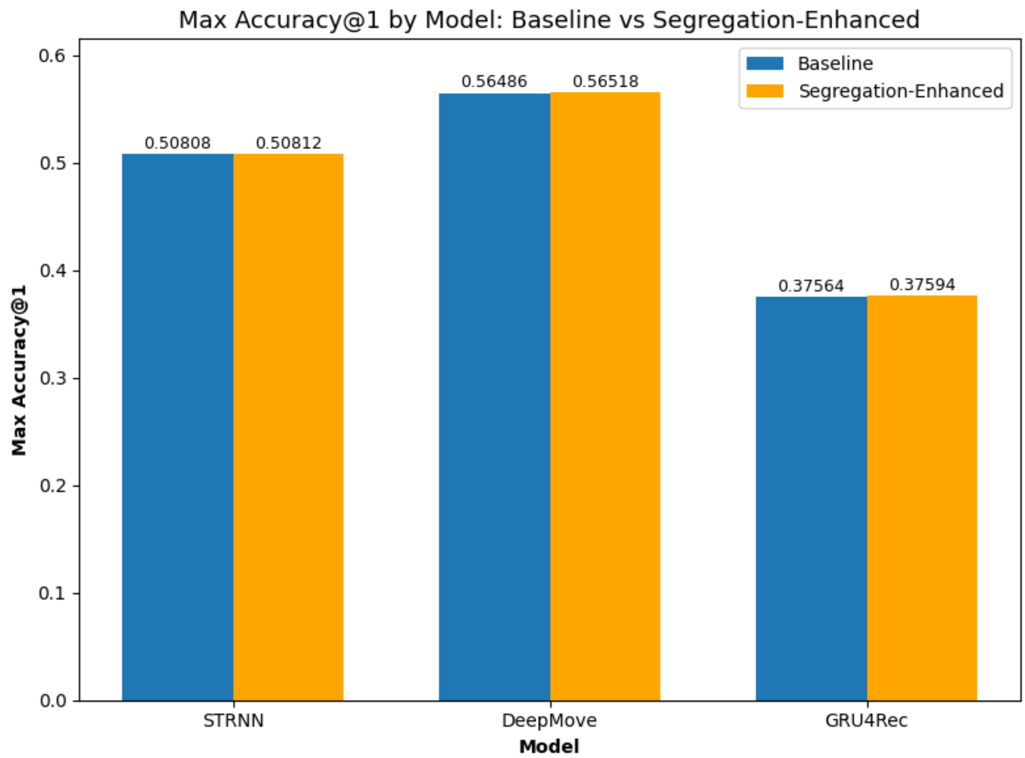

Figure 22: Maximum Top-1 Accuracy (Acc@1) comparison with Baseline vs Segregation-Based Models.

When evaluating Acc@1 performance across training epochs, the three models exhibit distinct learning behaviours. For GRU4Rec, both the baseline and the segregation-enhanced versions display considerable fluctuation during training. Performance for both versions declines rapidly after the initial epochs. For the ST-RNN model, the segregation-enhanced version initially performs slightly worse than the baseline but gradually converges and marginally surpasses it in the later epochs. In contrast, DeepMove demonstrates a more stable and consistent learning trajectory when enhanced with segregation metrics. The modified version consistently outperforms the baseline across multiple epochs and maintains a slight but steady lead by the end of training.

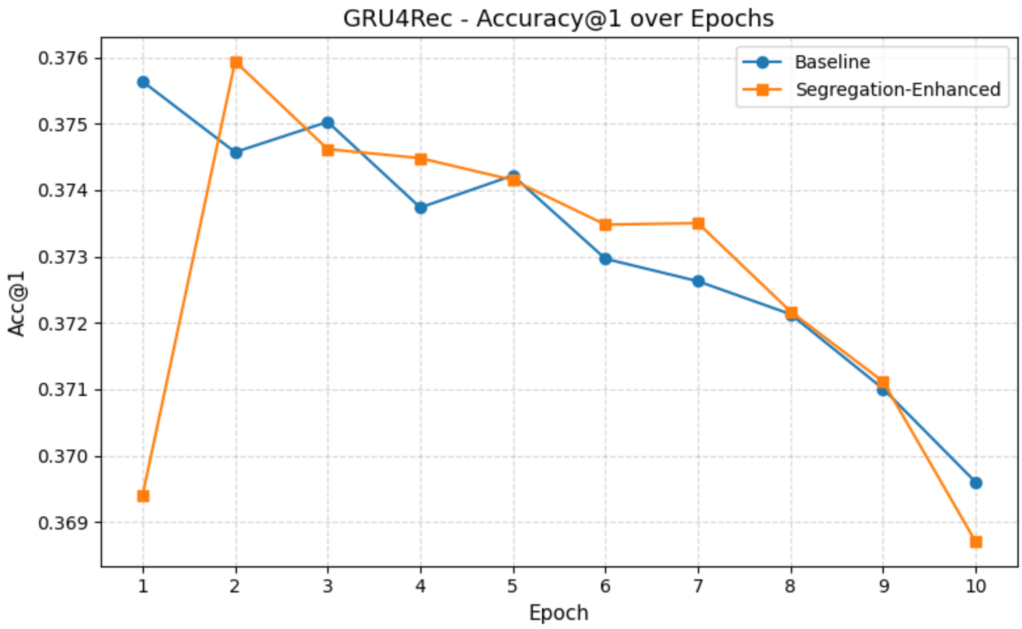

Figure 23: GRU4Rec Top-1 Accuracy Across Epochs: Baseline vs Segregation-Based Models.

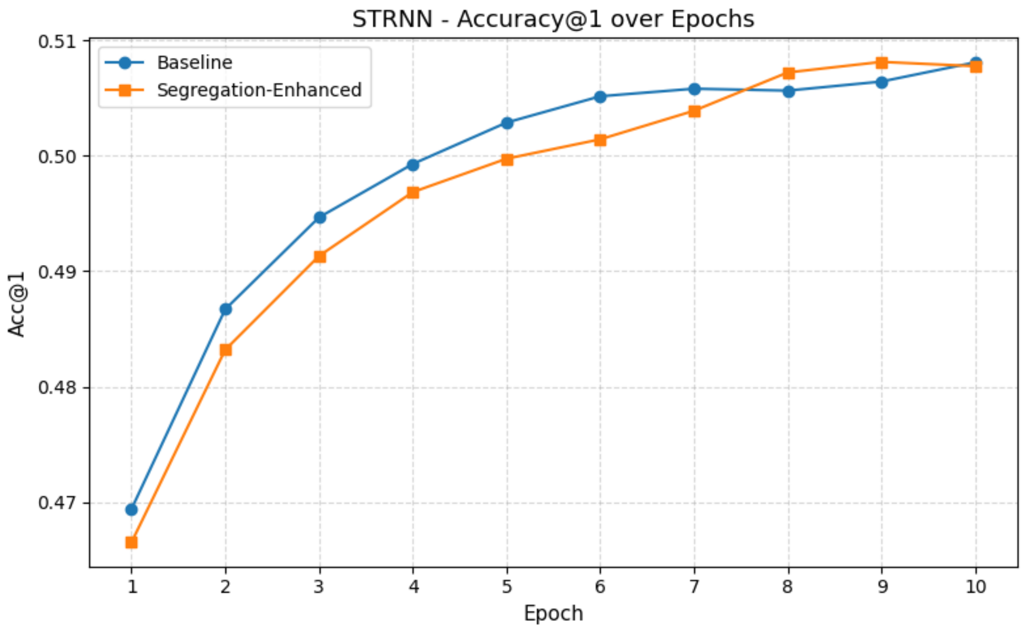

Figure 24: STRNN Top-1 Accuracy Across Epochs: Baseline vs Segregation-Based Models.

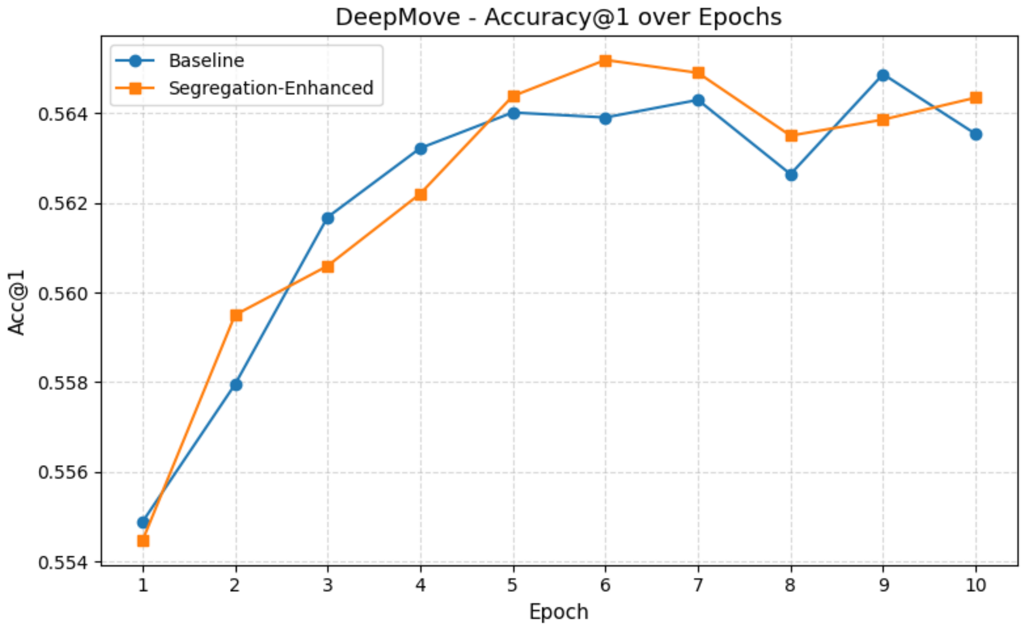

Figure 25: STRNN Top-1 Accuracy Across Epochs: Baseline vs Segregation-Based Models.

5 Discussion

5.1 Implication

The results of the Schelling-inspired simulation highlight the nonlinear nature of segregation in urban mobility. Even modest reductions in social tolerance can lead to a substantial decline in shared road usage, revealing the vulnerability of mixed-use infrastructure under conditions of preference-driven avoidance. Specifically, when the avoidance threshold reaches 0.4 or lower, grey roads, which represent unused or inaccessible segments, begin to dominate the map. Under these conditions, if new agents were introduced into neighbourhoods that match their income group and possess similarly low tolerance levels, they would likely face limited travel options. In such a scenario, individuals may opt not to travel at all, instead remaining within their immediate area, which could reinforce patterns of spatial isolation.

It is important to clarify that this simulation is not intended to be predictive. Rather, it serves as an exploratory tool designed to provide insights into how avoidance behaviour may influence experienced segregation. The results offer a preliminary view of how individuals might alter their mobility patterns in response to the presence of socially dissimilar groups. They also demonstrate how relatively small changes in social tolerance can generate disproportionate impacts on infrastructure usage and accessibility. These findings suggest that avoidance behaviour may play a significant role in shaping both urban mobility and social integration, and they may hold relevance for mobility prediction tasks that aim to incorporate social context.

While Schelling simulations have traditionally been employed as exploratory tools in urban and mobility studies (Ubarevičienė, van Ham and Tammaru, 2024), this research extends their application by modelling mobility-based avoidance behaviour using real-world road network data. To the best of the author's knowledge, this is the first study to apply the Schelling framework in this context. Although the simulation remains exploratory in nature, it provides a valuable foundation for future research next-location prediction studies.

In the context of next-location prediction conducted in this study, the results indicate that DeepMove (Attention Average Long User) achieves the highest Top-1 Accuracy (Acc@1), with a score of 56.49 percent, representing a 0.06 percent improvement over its baseline counterpart. However, the greatest performance gain following the integration of segregation-related variables is observed in GRU4Rec, which shows an improvement of 0.08 percent in Acc@1.

A plausible explanation for this difference lies in the architectural placement of the segregation metrics. In GRU4Rec, the socio-spatial features are introduced early in the network by adding the projected segregation vector directly to the item embeddings before they are processed by the GRU layer. This early integration may enable the network to learn temporal dependencies that are already conditioned on socio-spatial context. In contrast, both ST-RNN and DeepMove incorporate the segregation metrics only after the main recurrent or attention-based representations have been computed. This design difference suggests that perhaps introducing contextual information earlier in the learning pipeline may support richer representation learning and potentially enhance prediction accuracy. However, this hypothesis warrants further investigation, as prior studies have also explored the trade-offs between adding contextual features at the input or output stages in RNN-based models (Hoang, Haffari and Cohn, 2016; Smirnova and Vasile, 2017).

The modest improvements in prediction accuracy observed across the three models may be attributed to the sparsity of the data. One well-documented challenge in recurrent neural network (RNN) research is their limited ability to handle sparse user mobility traces, which has been a focus in recent studies aiming to improve model performance in such conditions (Yang et al., 2020; Deng et al., 2025). In this study, sparsity arises from two main factors. First, the underlying GPS mobility data is inherently sparse, particularly after applying quality filters. Second, the study adheres strictly to the definition of co-occurrence events proposed by Nilforoshan et al. (2023), where an encounter is only recorded if two users are within 50 metres of each other during a five-minute time window. As a result, the number of contact events is limited, further reducing the richness of user interaction signals.

Given this level of sparsity, the RNN models may struggle to fully leverage the additional segregation-based features. As noted by Zhou et al. (2021), spatio-temporal features and attention-based recurrent neural network mechanisms may not be sufficient to capture true travel preferences, particularly in cases where user–location interactions are extremely sparse. This limitation can introduce uncontrolled variance in both space and time, affecting the model's ability to accurately estimate users' visiting intentions and mobility patterns. Consequently, the models may be unable to effectively learn the complex decision-making processes that underpin human movement (Zhou et al., 2021; Huang et al., 2024).

Although the performance improvements over the baseline were modest in terms of accuracy percentage, the author argues that this line of research remains valuable, particularly given the underexplored nature of the Locomizer dataset in the context of mobility prediction. As noted by Fanelli (2011), it is important to report research findings even when results are not statistically significant, as they can still contribute to the broader academic conversation and guide future investigations.

Furthermore, although the accuracy improvements appear relatively small in percentage terms, their impact becomes more substantial at scale. For example, on a test set comprising over 1.6 million trajectories, GRU4Rec with segregation features correctly predicted approximately 1,300 more next locations than the baseline. DeepMove achieved a similar gain, with around 975 additional correct predictions, while ST-RNN recorded a more modest increase of approximately 160. These findings underscore the practical utility of incorporating socio-spatial signals, particularly in large-scale urban mobility systems where even marginal gains can translate into meaningful improvements in real-world applications.

Overall, one key implication of this study is the reaffirmation of the value of analysing co-occurrence patterns within next-location prediction research. These interactions provide important contextual information that can deepen our understanding of social dynamics embedded in human mobility. Moreover, they have significant potential to reveal the underlying structure of experienced segregation in urban environments (Liao et al., 2025; Yi et al., 2017; Nilforoshan et al., 2023; Hong et al., 2023). Identifying who interacts with whom, and where these interactions take place, offers valuable insights that can improve the performance and interpretability of prediction models by embedding them with socially meaningful context.

Another important consideration is the issue of data privacy. While the Locomizer dataset complies with GDPR regulations, it is crucial to acknowledge the ongoing privacy risks associated with mobility analysis, especially in tasks such as next-location prediction. For instance, synthetic trajectories generated by models may closely resemble real ones, potentially allowing malicious actors to infer sensitive patterns or identities (Luca et al., 2021; Nezhadettehad et al., 2025). As such, this study reinforces the need for continued attention to privacy-preserving methodologies in mobility research.

Lastly, beyond model development, this research carries broader practical implications for urban planning and policy-making. Stakeholders such as policymakers and city planners hopefully can leverage these findings to inform the design of infrastructure and services that promote equitable and inclusive access for all population groups. By incorporating behavioural mobility data into urban decision-making processes, it becomes more feasible to design environments that promote not only spatial efficiency but also spatial equality (Luca et al., 2021; Nezhadettehad et al., 2025).

5.2 Limitation & Future Research

This study faces several limitations, primarily related to data sparsity, missing variables, the operationalisation of co-presence, and the scope of methodological exploration, including hyperparameter tuning. First, the Locomizer dataset is constructed from check-in records rather than continuous GPS tracking. Due to privacy constraints and mobile battery limitations, users do not consistently log their locations, resulting in sparse sequences that can hinder the predictive performance of mobility models (Xue et al., 2021).

In addition, as previously discussed, this study adopts a strict definition of co-occurrence based on the framework proposed by Nilforoshan et al. (2023), in which two users are considered to have encountered each other only if they are located within 50 metres during a five-minute window. While this conservative threshold increases the precision of inferred interactions, it may also reduce the number of observable events, contributing further to sparsity in the dataset. Moreover, individuals without a stable place of residence or those with irregular work schedules may be underrepresented in the data, introducing potential sampling bias (Moro et al., 2021).

Another limitation lies in the socioeconomic categorisation of users, which is inferred based on the median income of each user's residential area. This introduces the risk of ecological fallacy, as not all residents of high-income neighbourhoods necessarily fall above the median income threshold, and the reverse also holds true (Wong, 2008). The use of neighbourhood-level income aggregates may therefore obscure within-area heterogeneity and lead to potential misclassification.

The study also does not consider key dimensions often examined in mobility and segregation research, particularly ethnicity and gender. Ethnicity remains central to discussions of urban segregation, yet it is not addressed here. Prior studies have highlighted how ethnic segregation in Helsinki is shaped by the spatial clustering of public housing and marginalised populations (Kwan, 2013; Tóth et al., 2021; Rosengren et al., 2024). Similarly, gendered mobility patterns are not examined in this research. For example, Ravalet (2006) observed that women tend to travel shorter distances than men, make more frequent shopping trips, and are more reliant on buses and walking.

These omissions are particularly significant given that travel behaviour is shaped by a complex interplay of economic, demographic, and social factors. Not all individuals have the same capacity or opportunity to move beyond their residential area. Factors such as transportation connectivity, commercial zoning, and the spatial distribution of amenities influence not only how people travel, but also their likelihood of encountering individuals from different social groups (Moro et al., 2021). These structural dimensions, however, are not explicitly addressed in this study. Moreover, even among residents of the same neighbourhood, levels of experienced segregation may vary due to differences in daily routines, occupational roles, and lifestyle preferences. Emerging trends, such as remote work, e-commerce, and on-demand service platforms, have further diversified individual mobility patterns (Moro et al., 2021; Liao et al., 2025), yet these evolving dynamics remain outside the scope of the current analysis.

A further limitation involves the use of co-presence as a proxy for socio-spatial interaction. While co-presence implies that individuals were in the same space at the same time, it does not reveal the nature, depth, or intent of the interaction. A casual conversation between friends, for example, is qualitatively different from a service transaction between strangers. Check-in data also does not differentiate between specific activities taking place at a location, such as a work meeting, lunch break, or shopping trip. These limitations call for a cautious interpretation of the findings and highlight the value of incorporating richer behavioural or semantic data in future research (Poudyal et al., 2024; Moro et al., 2021; Liao et al., 2025).

In addition, this study was constrained by limited model comparison and minimal hyper-parameter tuning due to time and computational constraints. Although prior research has explored the effects of introducing contextual features at different points in a recurrent neural network architecture (Hoang, Haffari and Cohn, 2016; Smirnova and Vasile, 2017), this study did not experiment with alternative configurations. Also this study did not assess the sensitivity of co-occurrence detection to variations in spatial and temporal thresholds, such as adjusting the 50-metre and five-minute criteria to better suit the nature of the Locomizer data.

Moreover, RNNs are known to struggle with long-range dependencies, often forgetting earlier information in long sequences, especially when data is sparse or transitions are complex (Lun et al., 2025; Feng et al., 2018). This limitation reduces their ability to capture long-term preferences in mobility prediction. More recent models, such as those based on transformers or graph neural networks, offer potential solutions to these challenges but were not explored here due to resource limitations.

In the context of the Schelling-inspired simulation, this study implements a constrained rerouting logic. If any segment along the original path exceeds the agent's social tolerance threshold, the system attempts to generate a maximum of three alternative shortest paths. This cap was introduced due to time and computational limitations. As a result, the simulation may not fully capture the complexity of avoidance behaviour, as it restricts the exploration of alternative routes. In contrast, other studies that apply graph-based Schelling models have employed significantly more exhaustive approaches. Some have allowed up to 50 routing attempts or continued rerouting until agents reached equilibrium, defined as the point at which each agent is satisfied with their location (Banos, 2012).

The simulation also does not incorporate dynamic spatial metrics to monitor changes in segregation across varying thresholds. Although Moran's I has been widely used in past research to quantify segregation levels (Hatna and Benenson, 2012), it was originally developed for grid-based environments and may not be suitable for real-world road networks. In this study, each edge may be classified as dominated by one group or marked as mixed, depending on usage patterns. Applying traditional spatial autocorrelation measures to such a network does not sufficiently reflect the nuanced transitions that occur across thresholds. Future research could explore more appropriate metrics to better evaluate socio-spatial segregation in road-based urban networks.

In terms of pathfinding this study uses Dijkstra's (1959) algorithm to compute shortest paths. While this method is widely established, recent work by Duan et al. (2025) introduces a new algorithm that claims to overcome the sorting bottleneck inherent in Dijkstra's approach. Incorporating this or other advanced pathfinding methods into future simulations could improve the efficiency and scope of rerouting, allowing for deeper exploration of agent behaviour and mobility patterns under social constraints.

Lastly, while Schelling-style simulations have traditionally served as exploratory tools in urban and mobility research (Ubarevičienė, van Ham and Tammaru, 2024), they also hold potential for integration into predictive modelling frameworks. Recent studies have shown that agent-based simulations can be used to inform the training of machine learning models by embedding behavioural priors into the learning process. This approach may help address concerns around the "black box" nature of predictive models by introducing interpretable mechanisms grounded in social theory (Xin, Zhou and Liu, 2025; Dyer et al., 2022; Sert, Bar-Yam and Morales, 2020; Yahia, Mansour and Toledo, 2025). Although this simulation-informed modelling strategy was beyond the scope of the present study, it represents a valuable direction for future research, particularly in efforts to bridge data-driven methods with behaviourally grounded insights.

6 Conclusion

The widespread use of smartphones and location-based services has led to the creation of large-scale mobility datasets. Predicting human mobility has become increasingly important for applications such as urban planning, traffic optimisation, and public health monitoring. While many models focus on spatiotemporal patterns, this study highlights the value of incorporating social context, particularly the concept of experienced segregation, into next-location prediction.

This thesis makes two main contributions. First, it introduces a novel adaptation of the Schelling model to simulate avoidance behaviour using a real urban road network in Helsinki, rather than a traditional grid format. This demonstrates that Schelling-inspired dynamics can be meaningfully applied to mobility contexts, offering behavioural insights into how individuals may navigate cities based on their preferences for social or economic similarity. Although there are limitations in how the simulation is evaluated, the findings provide a strong starting point for future research to refine the approach and validate the results.

Second, this study evaluates the effect of segregation-related features on the performance of three recurrent neural network (RNN) models: GRU4Rec, ST-RNN, and DeepMove. These features were embedded into the models to examine whether incorporating socio-spatial exposure improves prediction accuracy. Among the models tested, the best-performing configuration was the DeepMove model with attention-based long-term user context and added segregation metrics, achieving a Top-1 Accuracy (Acc@1) of 56.52 percent. However, the improvements associated with the segregation features were relatively small, ranging from 0.01 to 0.08 percentage points in Acc@1. This suggests that while the inclusion of socio-spatial context is conceptually valuable, more significant performance gains may require further hyperparameter tuning or the adoption of alternative architectures such as Transformer or Graph Neural Network models.

In conclusion, this research offers a new perspective on the integration of social behaviour and mobility prediction. It provides a methodological foundation for incorporating segregation-aware features into machine learning models and demonstrates the potential relevance of these features for understanding mobility patterns. The results have implications for future predictive frameworks as well as for policymakers seeking to address spatial inequality in Helsinki and similar urban environments.

7 Auto-Critique

One of the main reasons I was excited about this topic is that I had never previously worked on next-location prediction. I have always been intrigued by the idea that the mobility patterns of others might influence an individual's own movement, and this project presented a personal challenge to explore that concept further. Additionally, the opportunity to work with Locomizer's extensive and novel mobility dataset for Helsinki was something I could not pass up. The richness of this dataset enabled me to explore the role of experienced segregation in enhancing predictive models, which I found both technically and conceptually stimulating.

The main weakness of this study lies in the limited background research I conducted at the start. This constrained my ability to explore a wider range of models, methodological alternatives, and hyperparameter optimisation strategies. In hindsight, I underestimated the computational demands and time required to test multiple deep learning models on large-scale mobility data.

However, I believe the key strength of this project is its originality. To the best of my knowledge, this is the first study to integrate Schelling-inspired simulations and segregation-aware features into machine learning models for next-location prediction. If given the chance to do this again, I would allocate more time at the beginning for in-depth literature review and better time management, particularly to accommodate the heavy computational load.

Despite its limitations, I hope this thesis can still offer valuable insights for others working at the intersection of mobility prediction and social dynamics.

Auto-Critique word count: 246 words

References

Aoudjit, R., Belkadi, M., Daoui, M., Chamek, L., Hemrioui, S. and Lalam, M. (2013). Mobility Prediction Based on Data mining. International Journal of Database Theory and Application, 6(2).

Athey, S., Ferguson, B., Gentzkow, M. and Schmidt, T. (2021). Estimating experienced racial segregation in US cities using large-scale GPS data. In: Proceedings of the National Academy of Sciences.

Avetisov, V., Gorsky, A., Maslov, S., Nechaev, S. and Valba, O. (2018). Phase transitions in social networks inspired by the Schelling model. Physical Review, 98(3). doi:https://doi.org/10.1103/physreve.98.032308.

Banos, A. (2012). Network effects in Schelling's model of segregation: new evidence from agent-based simulation. Environment and Planning B: Planning and Design, 39(2), pp.393–405.

Bapierre, H., Jesdabodi, C. and Groh, G. (2015). Mobile Homophily and Social Location Prediction. arXiv (Cornell University). doi:https://doi.org/10.48550/arxiv.1506.07763.

Boodidhi, S. (2011). Using smoothing techniques to improve the performance of Hidden Markov's Model. UNLV Theses, Dissertations, Professional Papers, and Capstones. doi:http://dx.doi.org/10.34917/2349611.

Capanema, C.G.S., Oliveira, G.S. de, Silva, F.A., Silva, T.R.M.B. and Loureiro, A.A.F. (2023). Combining recurrent and Graph Neural Networks to predict the next place's category. Ad Hoc Networks, 138. doi:https://doi.org/10.1016/j.adhoc.2022.103016.

Chekol, A.G. and Fufa, M.S. (2022). A survey on next location prediction techniques, applications, and challenges. EURASIP Journal on Wireless Communications and Networking, 2022. doi:https://doi.org/10.1186/s13638-022-02114-6.

Cho, E., Myers, S.A. and Leskovec, J. (2011). Friendship and mobility. Proceedings of the 17th ACM SIGKDD international conference on Knowledge discovery and data mining.

Clark, W.A.V. and Fossett, M. (2008). Understanding the social context of the Schelling segregation model. Proceedings of the National Academy of Sciences, 105(11), pp.4109–4114. doi:https://doi.org/10.1073/pnas.0708155105.

Cornacchia, G. and Pappalardo, L. (2021). STS-EPR: Modelling individual mobility considering the spatial, temporal, and social dimensions together. Procedia Computer Science, 184, pp.258–265. doi:https://doi.org/10.1016/j.procs.2021.03.035.

Corrias, R., Gjoreski, M. and Langheinrich, M. (2023). Exploring Transformer and Graph Convolutional Networks for Human Mobility Modeling. Sensors, 23(10). doi: https://doi.org/10.3390/s23104803.

Crandall, D.J., Backstrom, L., Cosley, D., Suri, S., Huttenlocher, D. and Kleinberg, J. (2010). Inferring social ties from geographic coincidences. Proceedings of the National

Academy of Sciences, 107(52). doi:https://doi.org/10.1073/pnas.1006155107.

Daniel, J. and Martin, J. (2025). Speech and Language Processing: An Introduction to Natural Language Processing, Computational Linguistics, and Speech Recognition with Language Models, 3rd edition. [online] Available at: https://web.stanford.edu/ jurafsky/slp3.

Dao, T.-N., Le, D.V. and Yoon, S. (2019). Predicting Human Location Using Correlated Movements. Electronics, 8(1). doi:https://doi.org/10.3390/electronics8010054.

De Domenico, M., Lima, A. and Musolesi, M. (2013). Interdependence and predictability of human mobility and social interactions. Pervasive and Mobile Computing, 9(6), pp.798–807. doi:https://doi.org/10.1016/j.pmcj.2013.07.008.

Deng, B., Qu, B., Wang, P., Yang, D., Fankhauser, B. and Cudre-Mauroux, P. (2025). REPLAY: Modeling Time-Varying Temporal Regularities of Human Mobility for Location Prediction over Sparse Trajectories. IEEE Transactions on Mobile Computing, pp.1–14. doi:https://doi.org/10.1109/tmc.2025.3562669.

Dijkstra, E.W. (1959). A note on two problems in connexion with graphs. Numerische Mathematik, 1(1), pp.269–271. doi:https://doi.org/10.1007/bf01386390.

Duan, R., Mao, J., Mao, X., Shu, X. and Yin, L. (2025). Breaking the Sorting Barrier for Directed Single-Source Shortest Paths. In: Proceedings of the 57th Annual ACM Symposium on Theory of Computing. pp.36–44.

Dunning, R. and Moore, T. (2020). Defining and measuring empty and under-utilised dwellings in London. University of Liverpool with Dataloft.

Dyer, J., Cannon, P., Farmer, J.D. and Schmon, S.M. (2022). Calibrating Agent-based Models to Microdata with Graph Neural Networks. INET Oxford Working Paper No. 2022-30.

Elkind, E., Gan, J., Igarashi, A., Suksompong, W. and Voudouris, A.A. (2019). Schelling Games on Graphs. In: Proceedings of the Twenty-Eighth International Joint Conference on Artificial Intelligence (IJCAI-19). pp.266–272. doi:https://doi.org/10.24963/ijcai.2019/38.

Fanelli, D. (2011). Negative results are disappearing from most disciplines and countries. Scientometrics, 90, pp.891–904. doi:https://doi.org/10.1007/s11192-011-0494-7.

Feng, J., Li, Y., Zhang, C., Sun, F., Meng, F., Guo, A. and Jin, D. (2018). Deepmove: Predicting human mobility with attentional recurrent networks. Proceedings of the 2018 world wide web conference, pp.1459–1468. doi:https://doi.org/10.1109/tkde.2020.3006048.

Froehlich, J. and Krumm, J. (2008). Route Prediction From Trip Observations. SAE Technical Paper.

Gambetta, D., Mauro, G. and Pappalardo, L. (2023). Mobility constraints in segregation models. Scientific Reports, 13(1). doi:https://doi.org/10.1038/s41598-023-38519-6.

Gao, Q.-L., Zhong, C. and Wang, Y. (2024). Unpacking urban scaling and socio-spatial inequalities in mobility: Evidence from England. Environment and planning. B, Urban analytics and city science/Environment & planning. B, Urban analytics and city science. doi:https://doi.org/10.1177/23998083241234137.

Gibbs, H., Eggo, R.M. and Cheshire, J. (2023). Detecting behavioural bias in GPS location data collected by mobile applications. medRxiv.

Hai, N.T., Nguyen, H.-H. and Thai-Nghe, N. (2016). A mobility prediction model for location-based social networks. In: Intelligent Information and Database Systems: 8th Asian Conference, ACIIDS 2016, Da Nang, Vietnam, March 14–16, 2016, Proceedings, Part I 8. Springer Berlin Heidelber.

Hatna, E. and Benenson, I. (2012). The Schelling Model of Ethnic Residential Dynamics: Beyond the Integrated - Segregated Dichotomy of Patterns. Journal of Artificial Societies and Social Simulation, 15(1). doi:https://doi.org/10.18564/jasss.1873.

Hedman, L., Kadarik, K., Andersson, R. and Östh, J. (2021). Daily Mobility Patterns: Reducing or Reproducing Inequalities and Segregation? Social Inclusion, 9(2), pp.208–221. doi:https://doi.org/10.17645/si.v9i2.3850.

Helsinki Region Infoshare (2023). Helsinki metropolitan postal code areas - 2023 shp - Helsinki Region Infoshare. [online] Helsinki Region Infoshare. Available at: https://hri.fi/data/en$_{G}B/dataset/paakaupunkiseudun-postinumeroalueet/resource/617718ea - dcba - 4ae0 - a928 - 4b9642df76cf[Accessed1Sep.2025]$.

Hidasi, B. and Karatzoglou, A. (2018). Recurrent Neural Networks with Top-k Gains for Session-based Recommendations. Proceedings of the 27th ACM International Conference on Information and Knowledge Management. doi:https://doi.org/10.1145/3269206.3271761.

Hoang, C.D.V., Haffari, G. and Cohn, T. (2016). Incorporating Side Information into Recurrent Neural Network Language Models. Proceedings of NAACL-HLT 2016, pp.1250–1255. doi:https://doi.org/10.18653/v1/n16-1149.

Hong, Y., Martin, H. and Raubal, M. (2022). How do you go where? Improving next location prediction by learning travel mode information using transformers. In: Proceedings of the 30th International Conference on Advances in Geographic Information Systems. pp.1–10.

Hong, Y., Zhang, Y., Schindler, K. and Raubal, M. (2023). Context-aware multi-head self-attentional neural network model for next location prediction. Transportation Research Part C: Emerging Technologies, 156. doi:https://doi.org/10.1016/j.trc.2023.104315.

Huang, Z., Xu, S., Wang, M., Wu, H., Xu, Y. and Jin, Y. (2024). Human mobility prediction with causal and spatial-constrained multi-task network. EPJ Data Science, 13(1). doi:https://doi.org/10.1140/epjds/s13688-024-00460-7.

Huff, D.L. (1963). A Probabilistic Analysis of Shopping Center Trade Areas. Land Economics, 39(1), p.81. doi:https://doi.org/10.2307/3144521.

Järvinen, A. and Saarinen, E. (2021). POVERTY WATCH POVERTY WATCH REPORT FINLAND 2021. European Anti-Poverty Network Finland EAPN-Fin.

Jeong, J., Leconte, M. and Proutiere, A. (2016). Cluster-aided mobility predictions. IEEE INFOCOM 2016-the 35th annual IEEE international conference on computer communications.

Juhász, S., Pintér, G., Kovács, Á.J., Borza, E., Mónus, G., Lőrincz, L. and Lengyel, B. (2023). Amenity complexity and urban locations of socio-economic mixing. EPJ data science, 12(1). doi:https://doi.org/10.1140/epjds/s13688-023-00413-6.

Kang, J. (2025). Spatial Coordination of Electric Vehicle Adoption within the Urban Built Environment Using Machine Learning. Sustainable Futures, 10. doi:https://doi.org/10.1016/j.sftr.2025.100807.

Karhula, A., McMullin, P., Sutela, E., Ala-Mantila, S. and Ruonavaara, H. (2020). Rural-Urban Migration Pathways and Residential Segregation in the Helsinki Region. Finnish Yearbook of Population Research, [online] 55, pp.1–24. doi:https://doi.org/10.23979/fypr.96011.

Kim, J., Jeong, S., Park, G., Cha, K., Suh, I. and Oh, B. (2021). DynaPosGNN: Dynamic-Positional GNN for Next POI Recommendation. 2021 International Conference on Data Mining Workshops (ICDMW), 32, pp.36–44. doi:https://doi.org/10.1109/icdmw53433.2021.00012.

Krumm, J. (2008). A Markov Model for Driver Turn Prediction. SAE technical papers on CD-ROM/SAE technical paper series. doi:https://doi.org/10.4271/2008-01-0195.

Kwan, M.-P. (2013). Beyond Space (As We Knew It): Toward Temporally Integrated Geographies of Segregation, Health, and Accessibility. Annals of the Association of American Geographers, 103(5), pp.1078–1086. doi:https://doi.org/10.1080/00045608.2013.792177.

Laasonen, K. (2005). Route prediction from cellular data. Workshop on context-awareness for proactive systems (CAPS), 1617.

Laukkanen, M., Santtila, P., Jern, P. and Sandnabba, K. (2008). Predicting offender home location in urban burglary series. Forensic Science International, 176(2-3), pp.224–235. doi:https://doi.org/10.1016/j.forsciint.2007.09.011.

Law, S., Neira, M., Tanu, N., Keel, T., Jie, G., Tang, J. and Hu, D. (2025). Lab Notebook 6: Introduction to Human Mobility Analysis. UCL Department of Geography.

Liao, Y., Gil, J., Yeh, S., Pereira, R. and Alessandretti, L. (2025). The effect of limited mobility on the experienced segregation of foreign-born minorities. npj Sustainable Mobility and Transport, 2(1). doi:https://doi.org/10.1038/s44333-025-00046-4.

Liao, Y., Gil, J., Yeh, S., Pereira, R.H.M. and Alessandretti, L. (2025). Socio-spatial segregation and human mobility: A review of empirical evidence. Computers, Environment and Urban Systems, 117. doi:https://doi.org/10.1016/j.compenvurbsys.2025.102250.

Liu, Q., Wu, S., Wang, L. and Tan, T. (2016). Predicting the Next Location: A Recurrent Model with Spatial and Temporal Contexts. In: Proceedings of the Thirtieth AAAI Conference on Artificial Intelligence (AAAI-16).

Locomizer (2021). Audience Profiles - Footfall and Brand Affinity Points Product Guide.

Locomizer.

Locomizer (2025). Audience Profiles – Human Location Data Enrichment and Analysis Manual. Locomizer.

Luca, M., Barlacchi, G., Lepri, B. and Pappalardo, L. (2021). A Survey on Deep Learning for Human Mobility. ACM Computing Surveys (CSUR), 55(1), pp.1–44. doi:https://doi.org/10.1145/3485125.

Lun, M., Wang, P., Wu, S., Zhang, H., Cheng, S. and Lu, F. (2025). Predicting the Next Location of Urban Individuals Via a Representation-Enhanced Multi-View Learning Network. ISPRS International Journal of Geo-Information, 14(8). doi: https://doi.org/10.3390/ijgi14080302.

Luo, Y., Liu, Q.L. and Liu, Z. (2021). STAN: Spatio-Temporal Attention Network for Next Location Recommendation. Proceedings of the web conference 2021, pp.2177–2185.

Martin, H., Wiedemann, N., Reck, D.J. and Raubal, M. (2023). Graph-based mobility profiling. Computers, Environment and Urban Systems, 100. doi:https://doi.org/10.1016/j.compenvurbsys.2022.101910.

Moro, E., Calacci, D., Dong, X. and Pentland, A. (2021). Mobility patterns are associated with experienced income segregation in large US cities. Nature Communications, 12(1). doi:https://doi.org/10.1038/s41467-021-24899-8.

Nahhas, R.W. (2025). 5.19 Box-Cox outcome transformation — Introduction to Regression Methods for Public Health Using R. [online] Bookdown.org. Available at: https://www.bookdown.org/rwnahhas/RMPH/mlr-boxcox.html?utm
Accessed 23 Aug. 2025
.

Nezhadettehad, A., Zaslavsky, A., Abdur, R., Shaikh, S.A., Loke, S.W., Huang, G.-L. and Hassani, A. (2025). Predicting Next Useful Location With Context-Awareness: The State-Of-The-Art. ACM Transactions on Intelligent Systems and Technology.

Nilforoshan, H., Looi, W., Pierson, E., Villanueva, B., Fishman, N., Chen, Y., Sholar, J., Redbird, B., Grusky, D. and Leskovec, J. (2023). Human mobility networks reveal increased segregation in large cities. Nature, [online] 624(7992), pp.586–592. doi: https://doi.org/10.1038/s41586-023-06757-3.

Poliakov, A. (2018). Interest profile of a user of a mobile application.

Portugal, R.D. and Svaiter, B.F. (2010). Weber-Fechner Law and the Optimality of the Logarithmic Scale. Minds and Machines, 21(1), pp.73–81. doi: https://doi.org/10.1007/s11023-010-9221-z.

Poudyal, B., Pacheco, D., Oliveira, M., Chen, Z., Barbosa, H.S., Menezes, R. and Ghoshal, G. (2024). Dynamic predictability and activity-location contexts in human mobility. Royal Society Open Science, 11. doi:https://doi.org/10.1098/rsos.240115.

Qin, S.-M., Verkasalo, H., Mohtaschemi, M., Hartonen, T. and Alava, M. (2012). Patterns, Entropy, and Predictability of Human Mobility and Life. PLoS ONE, 7(12).

doi:https://doi.org/10.1371/journal.pone.0051353.

Ravalet, E. (2006). Segregation and daily mobility, an international comparison. WIT transactions on the built environment, 89, pp.491–500. doi:https://doi.org/10.2495/ut060481.

Reifman, A. and Keyton , K. (2012). Encyclopedia of Research Design. Sage Research Methods .

Rosengren, K., Kauppinen, T.M., Lilius, J., Rasinkangas, J. and Ruonavaara, H. (2024). Conflicting regional policy goals: accessibility and segregation in the Helsinki metropolitan area. Urban, planning and transport research, 12(1). doi:https://doi.org/10.1080/21650020.2023.2301063.

Schelling, T.C. (1971). Dynamic models of segregation. The Journal of Mathematical Sociology, 1, pp.143–186. doi:https://doi.org/10.1080/0022250x.1971.9989794.

Schneider, C.M., Belik, V., Couronné, T., Smoreda, Z. and González, M.C. (2013). Unravelling daily human mobility motifs. Journal of The Royal Society Interface, 10(84). doi:https://doi.org/10.1098/rsif.2013.0246.

Sert, E., Bar-Yam, Y. and Morales, A.J. (2020). Segregation dynamics with reinforcement learning and agent based modeling. Scientific Reports, 10(1). doi:https://doi.org/10.1038/s41598-020-68447-8.

Singh, A., Vainchtein, D. and Weiss, H. (2009). Schelling's Segregation Model: Parameters, scaling, and aggregation. Demographic Research, 21, pp.341–366. doi:https://doi.org/10.4054/demres.2009.21.12.

Smirnova, E. and Vasile, F. (2017). Contextual Sequence Modeling for Recommendation with Recurrent Neural Networks. Conference on Recommender Systems. doi:https://doi.org/10.1145/3125486.3125488.

Statistics Finland (2024). Median earnings for regular working hours of full-time wage and salary earners in central government were EUR 4,112 in 2023 — Statistics Finland. [online] Statistics Finland. Available at: https://stat.fi/en/publication/clmklvb9f4yux0cunww2id9hh.

Tang, Y., He, J. and Zhao, Z. (2024). Activity-aware Human Mobility Prediction with Hierarchical Graph Attention Recurrent Network. In: IEEE Transactions on Intelligent Transportation Systems .

Tobler, W.R. (1970). A Computer Movie Simulating Urban Growth in the Detroit Region. Economic Geography, 46, pp.234–240. doi:https://doi.org/10.2307/143141.

Tóth, G., Wachs, J., Di Clemente, R., Jakobi, Á., Ságvári, B., Kertész, J. and Lengyel, B. (2021). Inequality is rising where social network segregation interacts with urban topology. Nature Communications, [online] 12(1). doi:https://doi.org/10.1038/s41467-021-21465-0.

Tunström, M. and Wang, S. (2019). The segregated city: A Nordic overview. Nordic Council of Ministers.

Ubarevičienė, R., van Ham, M. and Tammaru, T. (2024). Fifty years after the Schelling's

Models of Segregation: Bibliometric analysis of the legacy of Schelling and the future directions of segregation research. Cities, [online] 147. doi:https://doi.org/10.1016/j.cities.2024.104838.

Vallejos, S., Berdun, L.S., Monteserin, A.J., Godoy, D.L., Armentano, M.G. and Schiaffino, S.N. (2025). Prediction of the next user location using personal tracking data. Expert Systems with Applications, 286. doi:https://doi.org/10.1016/j.eswa.2025.128125.

Wang, D., Pedreschi, D., Song, C., Giannotti, F. and Albert-László Barabási (2011). Human mobility, social ties, and link prediction. In: Proceedings of the 17th ACM SIGKDD international conference on Knowledge discovery and data mining. pp.1100–1108. doi: https://doi.org/10.1145/2020408.2020581.

Wang, H., Yu, Q., Liu, Y., Jin, D. and Li, Y. (2021). Spatio-temporal urban knowledge graph enabled mobility prediction. In: Proceedings of the ACM on interactive, mobile, wearable and ubiquitous technologies. pp.1–24.

Wang, J., Kong, X., Xia, F. and Sun, L. (2019). Urban Human Mobility. ACM SIGKDD Explorations Newsletter, 21(1), pp.1–19. doi:https://doi.org/10.1145/3331651.3331653.

Wang, W. and Osaragi, T. (2024). Learning Daily Human Mobility with a Transformer-Based Model. ISPRS International Journal of Geo-Information, 13(2). doi: https://doi.org/10.3390/ijgi13020035.

Wang, X., Cheng, T., Law, S., Zeng, Z., Ilyankou, I., Liu, J., Yin, L., Huang, W. and Jongwiriyanura, N. (2025). Into the Unknown: Applying Inductive Spatial-Semantic Location Embeddings for Predicting Individuals' Mobility Beyond Visited Places. arXiv preprint arXiv:2506.14070.

Wong, D.W. (2008). Ecological Fallacy. In: Encyclopedia of Geographic Information Science. [online] SAGE Publications, Inc. doi:https://doi.org/10.4135/9781412953962.n53.

Xin, Y., Zhou, Y. and Liu, Y. (2025). Prompts to layouts: Hybrid graph neural network and agent-based model for generative architectural design. Automation in Construction, 176. doi:https://doi.org/10.1016/j.autcon.2025.106253.

Xue, H., Salim, F.D., Ren, Y. and Oliver, N. (2021). MobTCast: Leveraging Auxiliary Trajectory Forecasting for Human Mobility Prediction. Advances in Neural Information Processing Systems, 34.

Yahia, S.H., Mansour, O. and Toledo, T. (2025). Incorporating domain knowledge in deep neural networks for discrete choice models. Transportation Research Part C: Emerging Technologies, 171.

Yang, D., Fankhauser, B., Rosso, P. and Cudré-Mauroux, P. (2020). Location Prediction over Sparse User Mobility Traces Using RNNs: Flashback in Hidden States! Proceedings of the twenty-ninth international joint conference on artificial intelligence, pp.2184–2190. doi:https://doi.org/10.24963/ijcai.2020/302.

Yi, F., Gu, Y., Wang, H., Sun, Y. and Sun, L. (2017). Mobility Pattern Based Relationship Inference from Spatiotemporal Data. GLOBECOM 2022 - 2022 IEEE Global

Communications Conference, pp.1–6. doi:https://doi.org/10.1109/glocom.2017.8253943.

Yu, J., Guo, L., Zhang, J. and Wang, G. (2024). A survey on graph neural network-based next POI recommendation for smart cities. Journal of Reliable Intelligent Environments, 10, pp.299–318. doi:https://doi.org/10.1007/s40860-024-00233-z.

Zakine, R., Garnier-Brun, J., Becharat, A.-C. and Benzaquen, M. (2024). Socioeconomic agents as active matter in nonequilibrium Sakoda-Schelling models. Physical Review E, 109(4). doi:https://doi.org/10.1103/physreve.109.044310.

Zhong, C., Aslam, N.S., Wang, Y., Zhou, Z. and Enaya, A. (2024). Anonymised human location data for urban mobility research. Centre for Advanced Spatial Analysis University College London.

Zhou, F., Dai, Y., Gao, Q., Wang, P. and Zhong, T. (2021). Self-supervised human mobility learning for next location prediction and trajectory classification. Knowledge-based systems, 228. doi:https://doi.org/10.1016/j.knosys.2021.107214.

8 Appendix

Main Code: https://colab.research.google.com/drive/—1wousC8j20nrzU65QBS6fxNAYT1J$_{W}Iw0$
?$usp = sharing$

Main dataset: https://drive.google.com/drive/folders/1-o2om3wGZQ1RQ-ty6Asywq6wahciPLmK
?usp=sharing

Main Mobility Data: https://drive.google.com/file/d/1tzLKwDZjIgCIX58eLLqZnJ4MtutBH3lI
/view?usp=sharing