Insights into urban spatial dynamics around Marmaray stations in Istanbul: Evidence from social media data

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Abstract

Key hubs like transfer centers facilitate intra-urban travel and accessibility in large cities. Understanding urban activity patterns around these hubs is vital for improving urban planning and infrastructure, thus enhancing livability. However, traditional research methods often fall short in capturing dynamic urban activities, whereas social media data provides rich insights into geographical locations, activity types, and movement patterns. This study uses location-based services from social media to analyze urban activity patterns around Marmaray stations on the Anatolian side of Istanbul. Analyzing Foursquare venue data within a 500-meter radius of 29 stations, Kernel density and K-means cluster analyses revealed four distinct activity clusters. These findings suggest varied urban activities at each station and help refine urban planning and transportation strategies.

Keywords: Activity patterns, Foursquare, Istanbul, location-based social network data, Marmaray stations

1. Introduction

The expansion of public transportation systems in large cities is a crucial strategy to alleviate traffic congestion and promote sustainable urban development. Public transportation hubs, transfer centers, and stations play a pivotal role in facilitating intra-urban journeys and offering accessibility to the activity spaces in their immediate surroundings. However, a better understanding of human mobility and activity patterns around these stations is needed to enhance urban planning, transportation infrastructure, and overall urban livability (Lang et al., 2020). The necessity arises because traditional research on individual activity-travel patterns over extended time periods has relied on labor-intensive surveys and questionnaires (Vilhelmson, 1999). While these methods have provided valuable insights, they are often costly and limited in covering a large number of individuals (Zhou et al., 2018). Additionally, there are data-related constraints in the analysis of urban space and dynamics, such as currency, availability, accessibility, representativeness, objectivity, and diversity of the data.

On the other hand, the proliferation of location-based services in social media applications, which has ushered in an era where people willingly share their activity-related choices, such as check-ins on various platforms like Facebook, Foursquare, and X (formerly Twitter), has emerged as an alternative data source. This has led to the accumulation of a high volume of user-generated data, offering valuable insights into human movement and activity patterns. This data source not only contains specific geographic information but also provides insights into how different types of activities are chosen for various purposes, activity categories, and movement patterns.
In recent studies (Hasan et al., 2013; Zhou and Zhang, 2016; Üsküplü et al., 2020; Ebrahimpour et al., 2020; Mohammadbagherzadeh & Terzi, 2022), location-based data has gained increasing interest due to its rich information, linking each geographical record to a venue category that explains the reasons behind the activities. Consequently, this has opened doors to novel applications, from recommendation systems for physical locations to travel route optimization. Beyond these applications, the data has the potential to revolutionize fields such as travel demand modeling, urban planning, epidemiology, security, and health monitoring (Ling-Yin et al., 2012).

In this context, this research investigates the activity patterns around the stations of the Marmaray mass rapid transit railway system on the Anatolian side of Istanbul, one of the important public transportation lines, by exploring the potential of using data from location-based social networks, specifically venue data from Foursquare. The research aims to answer two key questions:

• What are the differences among Marmaray stations in Istanbul in terms of the distribution of activity spaces?

• What characteristics can be observed through venue data in the surroundings of these stations?

2. Exploring urban spatial dynamics through location-based social networks

This chapter presents the theoretical background for the research, which extends to the activity spaces and activity patterns in urban spatial dynamics, location-based social networks, and their innovative perspectives on the analysis of spatial dynamics within urban research.

2.1. Activity spaces as spatial components of urban dynamics

Activity space is an important component in urban dynamics since it traces its origins to the conceptualization of social space and the analysis of urban time-space patterns in behavior. Activity spaces, defined by Horton and Reynolds (1971) as "the subset of urban locations with which an individual interacts due to their activities," encompass both the physical locations and the subjective experiences within these spaces, reflecting a blend of objective spatial structure and individual urban interactions (Golledge and Stimson, 1997). The concept of activity space has evolved from behavioral geography over time and has been defined with various terminologies in different contexts, such as "activity system" (Chapin, 1968), "awareness space" (Brown and Moore, 1970), and "action space" (Horton and Reynolds, 1971). Activity space is a multidimensional concept with spatial, temporal, and cognitive dimensions (Wang et al., 2012). These dimensions are evident in the diverse ways individuals use urban space, influenced by factors such as mobility and access.

To understand the multidimensional structure of activity spaces, the use of the concept in urban research has also varied, with methodologies including the standard deviational ellipse (SDE), network-based approaches, kernel density estimations, minimum convex-hull polygons (MCP), and other methods (Patterson and Farber, 2015). Each of these approaches offers a different perspective on understanding activity spaces, but within this research, it is important to elaborate more on kernel density estimation (KDE). Each of these approaches offers a different perspective on understanding activity spaces, but within this research, it is important to put more elaboration on kernel density estimation (KDE), as a data smoothing technique, which plays a significant role in examining activity spaces by interpolating point data to create a continuous surface (Bailey and Gatrell, 1995). Since it offers insights into the intensity and distribution of activities within urban spaces with its this feature, it has been used in different research studies (Kwan, 2000; Axhausen, 2002; Kamruzzaman et al., 2011).

Furthermore, the advancements in Geographic Information Systems (GIS) and the availability of extensive geographical data have opened up new opportunities for researchers to digitally define activity spaces. This potential has expanded beyond mobile phone data to encompass crowdsourced information like social media and Points of Interest (POI) data (Yuan et al., 2012). These sources, including social media, POI data, websites, and various online platforms relying on voluntary data sharing, have primarily been utilized for modeling aspects of urban activity patterns, mobility, land usage, location preferences, as well as for conducting semantic and perceptual studies related to spatial analysis (Niu and Silva, 2023). In this context, exploring these new sources of data and methodologies is considered important for gaining a deeper understanding of activity spaces and providing insights into the dynamics of the urban environment.

2.2. Digital footprints for urban spatial dynamics: Location-based social networks

User-generated content has emerged as a critical source for investigating interactions with urban spaces and explaining how people engage with their environment in daily life. This phenomenon demands new theoretical perspectives, as suggested by Cope (2015), to gain a deeper understanding of these interactions. The integration of digital services into daily urban life, noted by Dunkel (2015), offers a valuable lens for exploring the various components and socio-spatial dynamics of urban environments. The advancement of GPS technology has introduced a novel dimension to urban analysis by linking user-generated content with specific geographic locations within the urban landscape. This process encompasses recording, sharing, reviewing, and recommending spaces and functions, significantly enhancing the comprehension of city dynamics (Arribas-Bel, 2014). Within this context, location-based services and social networks represent a convergence of internet-connected devices, location-based technologies, and GIS (Brimicombe, 2002). Social networks, as virtual social structures, are formed through connections such as friendships, shared interests, and collective knowledge among users. These networks enable users to express thoughts, opinions, activities, and interests.

The integration of location-based data into social networks, creating location-based social networks (LBSNs), bridges the gap between online interactions and real-world environments. This integration allows tracking users' interests and behaviors through their location information within these networks (Zheng, 2011). Moreover, LBSNs facilitate the sharing of location-specific data within an existing social network and the creation of new networks where users connect based on physical location. Consequently, LBSNs gather extensive databases containing variables such as text, images, and quantitative data. The database structure, formed by users' location history and the shared archive of geo-tagged content, is instrumental in understanding users' preferences, behaviors, and activities (Marti et al., 2019).

The functionalities and content of each social network vary, but commonalities exist in how they establish networks of contacts and allow users to register with a profile, create, share, or interact with content. Bernabeu-Bautista et al. (2021) categorize current social networks into five types: contact-focused networks like Facebook or LinkedIn, microblogging networks such as X or Tumblr, multimedia sharing networks including Instagram, Flickr, Pinterest, or YouTube, specialized networks like Airbnb, Google Places, Foursquare, or Sina Weibo, and instant messaging services such as Telegram or WhatsApp. Each category serves distinct user interactions and needs. According to Bernabeu-Bautista et al. (2021), the suitability of these networks for urban studies hinges on four key characteristics: precise geolocation of data, accessibility and privacy of the data, the ability of data variables to reflect urban and social activity, and predominant use on mobile devices. These aspects enable the analysis of user behaviors, interactions, mobility, and activity patterns within urban spaces in real-time and dynamic contexts. Choosing the right social network for urban research depends on the study's goals and the required data format, be it text, images, opinions, or quantitative data. In this way, LBSNs have demonstrated extensive potential in urban research. For instance, Lee, Wakamiya, and Sumiya (2013) utilized social media data to discern behavioral patterns and types of spaces within cities. This data, emerging as a by-product of everyday life, contrasts with planned surveys, providing a free and widely accessible resource for urban research, especially valuable in locations with limited official data (Arribas-Bel, 2014). However, the computational exploration of this data often lacks a well-established theoretical or philosophical framework, indicating a need for urban research to establish its own methodological framework to develop a more comprehensive understanding of urban dynamics.

Focusing on geo-tagged data obtained from different LBSN platforms and methods, various studies have utilized it to examine urban dynamics through activity and mobility patterns (Table 1). Liu et al. (2014) focused on intra-urban trip patterns and spatial interactions using Weibo's check-in data, employing a gravity model and particle swarm optimization (PSO) to analyze the data. This approach allowed for an understanding of movement patterns within urban environments. Hasan et al. (2013) suggested that social media users tend to visit different places with decreasing regularity following Zipf's law and analyzed Foursquare check-in data posted on Twitter. In a subsequent study, Hasan et al. (2014) shifted their focus to user-specific activity patterns using geo-tagged tweets from Twitter by applying Latent Dirichlet Allocation (LDA), a method that helped identify patterns based on the content of tweets.

Zhou and Zhang (2016) also explored activity intensities in a temporal context by combining data from Twitter and Foursquare. They analyzed geo-tagged tweets with related Foursquare categories, using hotspot and spatial clustering analyses to study the temporal dynamics of urban activities. Zhou and Xu (2017) extended this approach to the spatio-temporal evolution of natural (heavy precipitation) and specific social events in New York City, employing density-based spatial clustering (DBSCAN), KDE, and sentiment analysis on various features of Twitter data to understand the city dynamics.

Cui et al. (2018) focused on the temporality of frequently visited places by integrating Weibo check-in data with survey data. They used a distance-based clustering algorithm to understand how frequently certain locations were visited and the patterns associated with these visits. Yang et al. (2019) studied human mobility and activity patterns at the group level using geo-tagged Weibo messages. Their approach involved multiple spatial distribution analyses, providing insights into group behaviors in urban spaces. Üsküplü et al. (2020) analyzed activity patterns in parts of historical districts in Istanbul using Foursquare data, specifically POI and check-in data. They applied hotspot and spatial clustering analyses to understand the activities within these culturally significant areas.

Ebrahimpour et al. (2020) focused on socio-geographic human mobility patterns using geo-located Weibo data. They utilized KDE and DBSCAN to analyze the spatial and social aspects of human mobility. Mohammadbagherzadeh and Terzi (2022) conducted a study on activity patterns around metro stations in Istanbul using Foursquare's POI data through KDE and K-means cluster analysis. Since their case area involves the Marmaray stations on the European side of the city, it is considered an important example in terms of both the case, methodology, and the results for comparison among the Marmaray stations on both sides. Lastly, Niu and Silva (2023) employed hotspot analysis on geo-tagged tweets from Twitter to explore spatial, temporal, and demographic patterns of urban activities, offering a comprehensive view of how different demographic groups interact with urban spaces.

In conclusion, this comprehensive exploration of urban research through LBSNs emphasizes the common use of density-based clustering methods for analyzing urban activity and mobility patterns. The studies reviewed in this chapter demonstrate a diverse context of approaches using geo-tagged data from various LBSNs, which has been instrumental in revealing complex patterns of urban life. The different applications of LBSNs in urban studies underscore their potential in shaping our understanding of urban environments and make them an invaluable tool in the realm of urban research.

Table 1. Studies of activity and mobility patterns inference from geo-tagged social media

Studies	Research focus	Data source	Data used	Method/ Algorithm
Liu et al. (2014)	Intra-urban trip patterns and spatial interactions	Weibo	Check-in data	Gravity model and PSO
Hasan et al. (2013)	Activity and mobility patterns	Foursquare and Twitter	Foursquare check-in data posted in Twitter	KDE and statistical distribution analysis
Hasan et al. (2014)	User-specific activity patterns	Twitter	Geo-tagged tweets	LDA
Zhou and Zhang (2016)	Activity intensities in temporal context	Twitter and Foursquare	Geo-tagged tweets and their category links to Foursquare	Hotspot and spatial clustering analyses
Zhou and Xu (2017)	Spatio-temporal evolution of natural and social events	Twitter	Various features pf Twitter data	DBSCAN, KDE, sentiment analysis
Cui et al. (2018)	Temporality of frequently visited places	Weibo and survey	Check-in and survey data	DBSCAN
Yang et al. (2019)	Human mobility and activity patterns at group level	Weibo	Geo-tagged Weibo messages	Multiple spatial distribution analyses
Üsküplü et al. (2020)	Activity patterns of historical districts	Foursquare	POI and check-in data	Hotspot and spatial clustering analyses
Ebrahimpour et al. (2020)	Socio-geographic human mobility patterns	Weibo	Geo-located Weibo data	KDE and DBSCAN
Mohammadbagherzadeh and Terzi (2022)	Activity patterns around metro stations	Foursquare	POI data	KDE and K-means cluster analysis
Niu and Silva (2023)	Spatial, temporal, and demographic patterns of urban activities	Twitter	Geo-tagged tweets	Hotspot analysis

3. The case area: Marmaray stations

Istanbul, with a population exceeding 15 million according to TUIK (2022), is Turkey's largest city, covering an area of 5,461 square kilometers. These characteristics make Istanbul the most densely populated city in Turkey, with around 20% of the nation's population residing within its boundaries. The city is divided into two parts by the Bosphorus, with one side in Europe and the other in Anatolia. Throughout Istanbul's history, infrastructure and transportation projects have played a significant role in the city's expansion and have influenced its spatial and social aspects.

In this context, the Marmaray mass rapid transit railway system, one of the mega-infrastructure projects, enhances accessibility to activity spaces in its immediate vicinity. It has a total of 43 stations, spanning from Halkalı to Sirkeci on the European side (14 stations) and from Üsküdar to Gebze on the Anatolian side (29 stations). By focusing on the stations on the Anatolian side and the different types of venues around them, this research aims to gain insights into how social media data can provide evidence of urban spatial dynamics in response to transportation infrastructure (Figure 1).

Figure 1. Location of the case area in Istanbul

4. Data and Methodology

This research focuses on integrating geo-tagged social media data, specifically venue data from Foursquare, to develop insights into the spatial dynamics around Marmaray stations through activity spaces and patterns. Accordingly, the methodology of this research comprises three sequential phases with two main analyses (Figure 2):

- Data Collection: Retrieving the data through the use of Social Network’s Application Programming Interface (API) for the analyses.

- Kernel Density Estimation: Revealing the spatial distribution of venues/activity spaces' density.
- K-means Cluster Analysis: Evaluating the clustered characteristics of the stations

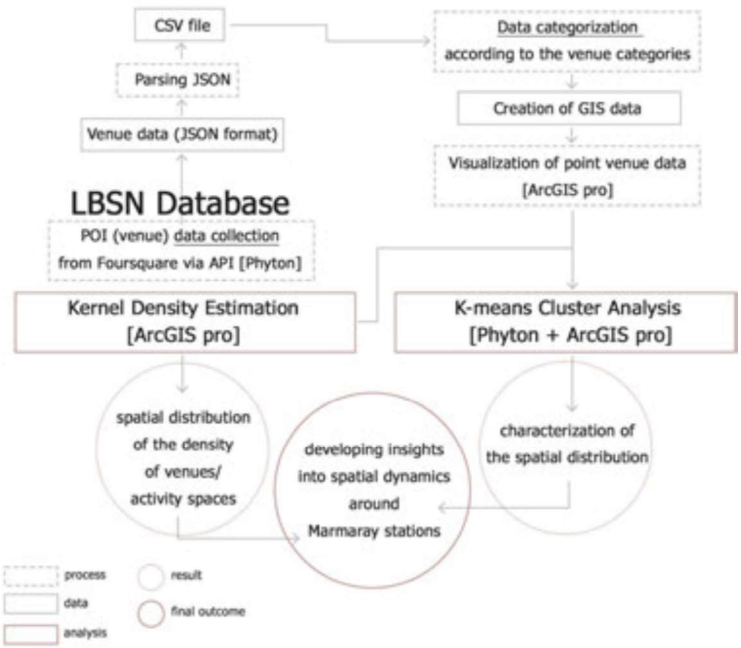

Figure 2: Flowchart of the research design

4.1. Data Collection

As part of this research, venue data from Foursquare—a location-based social network—was employed due to its easily manageable content, inclusion of geographical information, and public accessibility for researchers. To gather venue data within a 500-meter radius of 29 Marmaray stations, a search query was executed through an API, which is an interface that enables users to integrate with data from various social media platforms, using the Python programming language.

Since the Foursquare Public Search API allows a maximum of 50 venues per a single search, the search radius was progressively expanded from 50 to 500 meters in increments of 50 meters. Consequently, the search was conducted ten times for each category. The Foursquare categories searched include: Arts and Entertainment, Dining and Drinking, Landmarks and Outdoors, Retail, Sports and Recreation, Business and Professional Services, Community and Government, Health and Medicine, and Travel and Transportation. The resultant dataset includes venue points with details such as venue ID, venue name, location (latitude and longitude), category name/id, and sub-category name/id. Duplicated venue points within the overlapping search radii were removed based on their venue IDs, resulting in a total of 4,566 unique venues. The dataset, encompassing nine categories as shown in Table 2, was converted from JSON format into a CSV file for data analysis in ArcGIS.

Table 2. Distribution of the searched categories

Venue Categories	# of venues	% of venues
Arts and Entertainment	344	7.53 %
Dining and Drinking	1939	42.46 %
Landmarks and Outdoors	315	6.90 %
Retail	1686	36.92 %
Sports and Recreation	192	4.21 %
Business and Professional Services	76	1.66 %
Community and Government	6	0.13 %
Health and Medicine	7	0.15 %
Travel and Transportation	1	0.02 %
ALL	4566	

4.2. Data Analysis

In the data analysis process, two main analyses were conducted: Kernel density estimation and K-means cluster analysis, respectively.

4.2.1. Kernel Density Estimation

As mentioned earlier in the literature review chapter regarding its application in urban research, KDE is a widely used method in spatial analysis. It is employed to create a continuous density surface that visualizes the spatial clustering of point or line features in a two-dimensional space (Wilson and Gerard, 2019). To generate a smooth curve within the venue dataset obtained from Foursquare and identify the most significant densities in ArcGIS Pro, several steps were taken. First, the categories "Community and Government, Health and Medicine, Travel and Transportation" were excluded due to their limited venue data. The point venue data from the remaining six categories were mapped in ArcGIS Pro, as illustrated in Figure 3, with the Marmaray line divided into four sections to provide a more detailed view of distribution. Subsequently, KDE was applied to all venues and separately to venues within these six categories (Figure 5).

4.2.1. K-means Cluster Analysis

The K-means algorithm is well-known for its ability to cluster data into n groups, each with approximately equal variance, while minimizing a measure called inertia or the sum of squares within each cluster (Jain et al., 1999). In this direction, to categorize and comprehend the types of activities and their distribution across different stations, the Python library Scikit-learn was used for K-means cluster analysis. Within the scope of this research, the results of the elbow method, using inertia, were more suitable, with the optimum cluster value (k) being determined as four (Figure 4). The clusters were then visualized in ArcGIS Pro (Figure 6), and the results were evaluated further.

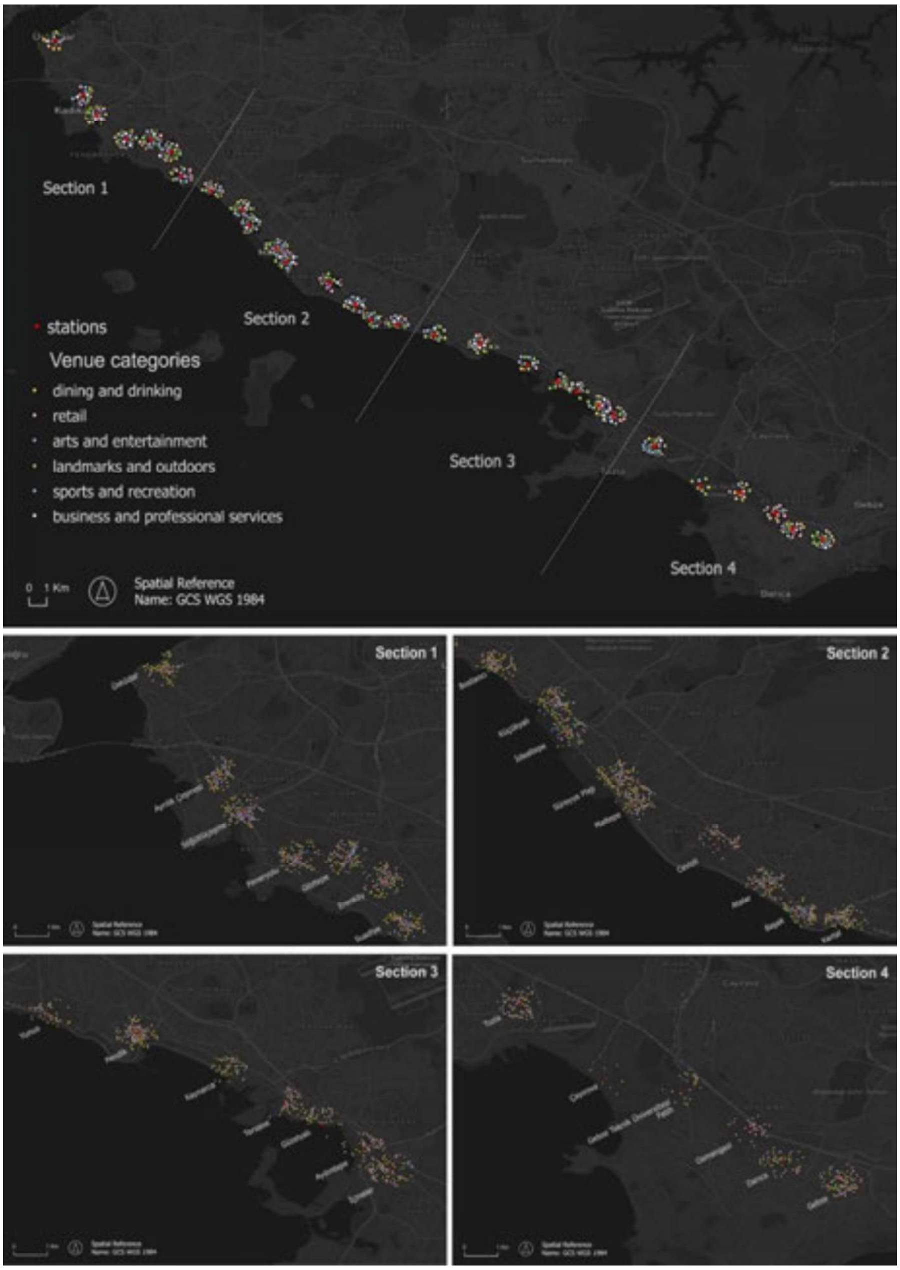

Figure 3. Visualization of point venue data

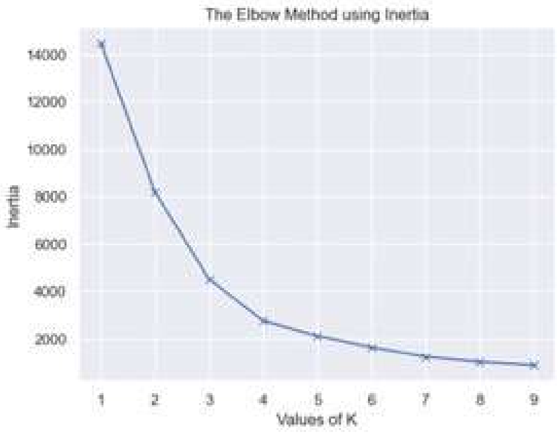

Figure 4. Optimum cluster value (k) according to Elbow Method

5. Results and Discussion

In this chapter, the results and the further discussion are presented in two parts: distribution, and clustered characteristics of activity spaces around Marmaray stations, as parallel to the data analysis.

5.1. Distribution of activity spaces/venues around Marmaray stations

The results indicate significant venue densities around several stations, including Ayrılık Çeşmesi-Söğütlüçeşme in Kadıköy, Göztepe-Erenköy, Küçükyalı-İdealtepe, Süreyya Plajı-Maltepe, and Başak-Kartal. Conversely, venues around Gebze Teknik Üniversitesi/Fatih and Çayırova do not form any significant densities.

Arts and recreation venues create notable densities along the stations Ayrılık Çeşmesi, Söğütlüçeşme, Feneryolu, Göztepe, Erenköy, Suadiye, and Başak-Kartal. Dining and drinking venues show remarkable densities from Göztepe to Maltepe, with the highest concentration at Maltepe. Subsequently, high densities are observed at Ayrılık Çeşmesi and Başak-Kartal. Landmarks and outdoor venues form significant densities at Küçükyalı-Maltepe, Başak-Kartal, and Göztepe-Suadiye. Retail venues show the highest densities at Göztepe-Suadiye, followed by Pendik and İdealtepe-Maltepe. Sports and recreation venues form significant densities at Atalar-Kartal, İdealtepe-Maltepe, and Feneryolu-Suadiye. Lastly, business and professional service venues create significant densities at Güzelyalı-İçmeler and in the areas around Söğütlüçeşme-Göztepe, Kartal, and İdealtepe (Figure 5).

Considering the density distribution of venues along the entire Marmaray line on the Anatolian side, retail venues, while forming significant densities at certain stations, are relatively more evenly spread across all stations. Additionally, a noticeable decrease in dining, drinking, and sports and recreation venues beyond the Pendik station highlights a distinct shift in venue density, giving Pendik and similarly Tuzla stations a unique character compared to other stations. When these results are compared with the existing study by Mohammadbagherzadeh and Terzi (2022), despite differences in venue categories and analysis processes, similar concentrations of retail venues at stations like Göztepe and Suadiye show high density of shop and service venues found around the Sirkeci station. Furthermore, the European side exhibits strong densities of outdoor and entertainment venues at stations like Sirkeci, Bakırköy, and Ataköy, reflecting a pattern similar to that of the Anatolian side's clusters around stations like Küçükyalı-Maltepe and Göztepe-Suadiye. These similarities in findings underscore the need for a more comprehensive evaluation of all the stations along the entire Marmaray line, including the European side.

5.2. Clustered characteristics of activity spaces/venues around Marmaray stations

The K-means cluster analysis of activity spaces around Marmaray stations, as shown in Figure 6, has categorized the stations into four distinct clusters, each demonstrating unique characteristics in terms of venue distribution. The statistical distribution of venue categories for each cluster is also presented in a boxplot (Figure 7).

Cluster 0, comprising five stations (Cevizli, Pendik, Tersane, Aydıntepe, and Osmangazi), which constitute approximately 17% of all stations, has predominantly a retail-based character, with a considerable number of dining and drinking venues. These stations likely serve as local commercial hubs.

Although their characters are different, clusters 1 and 3 are the closest clusters to each other in terms of the number of stations they have. Cluster 1, with 13 stations (Söğütlüçeşme, Feneryolu, Göztepe, Erenköy, Küçükyalı, Maltepe, Başak, Kaynarca, Güzelyalı, İçmeler, Tuzla, Darıca, and Gebze), accounts for approximately 45% of all stations. In this cluster, retail and dining and drinking venues show a balanced distribution. Cluster 2, with only one station, Çayırova, features limited dining and drinking, landmarks and outdoors, sports and recreation, and lacks arts and entertainment as well as business and professional services. This cluster represents unique characteristics, possibly indicative of a less developed area in terms of urban functions.

Cluster 3 includes 10 stations (Üsküdar, Ayrılık Çeşmesi, Suadiye, Bostancı, İdealtepe, Süreyya Plajı, Atalar, Kartal, Yunus, and Gebze Teknik Üniversitesi/Fatih), making up approximately 35% of all stations. This cluster is predominantly characterized by dining and drinking venues, followed by retail, indicating vibrant commercial and social life. Overall, arts and recreation, landmarks and outdoors, sports and recreation, and business and professional services venues do not have significantly impact cluster formation and show a relatively balanced distribution, except for cluster 2 as an outlier. Therefore, the clusters are primarily characterized by retail, and dining and drinking venues.

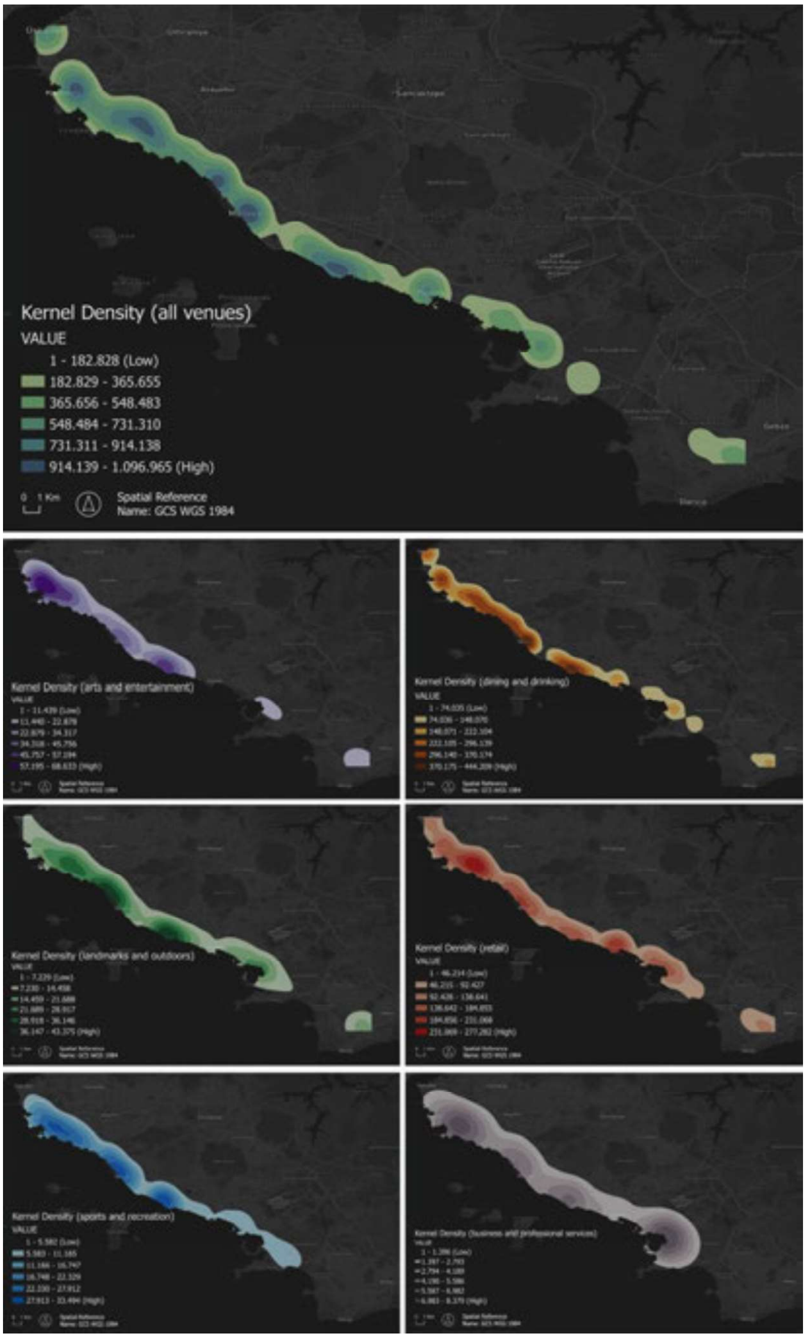

Figure 5. Distribution of the activity spaces around the stations

Figure 6. Clustered characteristics of activity spaces around the stations

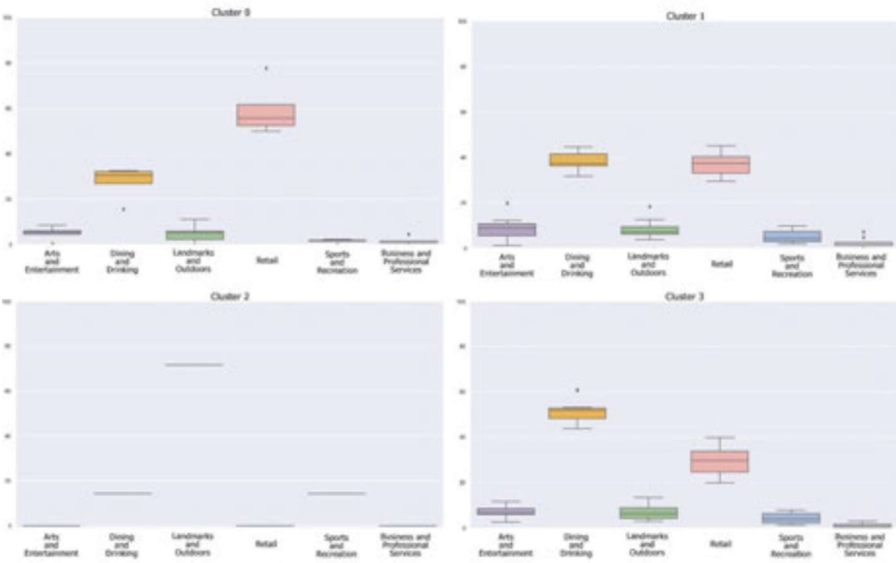

Figure 7. Distribution of categories for each cluster

6. Conclusion

The expansion of public transportation in large cities, particularly the role of transportation hubs like the Marmaray stations in Istanbul, is critical for sustainable urban development and reducing traffic congestion. These hubs are central to accessing nearby activity spaces, yet there is a knowledge gap in understanding their relationship with human mobility and activity patterns through different data and methodologies. This study addresses this gap by using Foursquare venue data to analyze the spatial distribution of activities around these stations.

The findings reveal significant densities of various venues around specific Marmaray stations, with notable clusterings in the characterization of these densities. For instance, cluster 0, including stations like Cevizli and Pendik, predominantly features retail activities. Cluster 1, with stations such as Söğütlüçeşme and Göztepe, exhibits a balanced mix of retail and dining venues. On the other hand, cluster 3, including stations like Üsküdar and Bostancı, is marked by a strong presence of dining and drinking venues and indicates areas with vibrant commercial and social life. These examples demonstrate how clusters differ in their urban function characteristics and the valuable insights offered by LBSN data into urban research more broadly (Dunkel, 2015). This data allows for precise estimation of geographic densities at both global and local scales and facilitates geographic clustering to identify areas with similar characteristics.

However, while the data used in this research was publicly accessible, challenges such as access to, reliability, and management of LBSN data can pose significant limitations. Particularly in this research, findings highlight the need for a more comprehensive evaluation of all stations on the Marmaray line, including those on the European side. Moreover, the study currently focuses only on the spatial dynamics formed by activity spaces. Future studies could extend to include social, perceptual, and/or temporal dimensions to thoroughly discuss urban dynamics, considering the potential of LBSNs in these dimensions. These points as limitations of the current research can also provide clues and direction for future studies.

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Track 17: Risks

RISKS - Planning for adaptive capacity: disasters, uncertainty, long-term problems, preparedness and responsiveness

Chairs:

- Lionel Prigent, Université de Bretagne occidentale
- Ward Rauws, University of Groningen
- Daniel Zwangsleitner, TU München
- Rumeysa Ceylan, Istanbul Teknik Üniversitesi

Keywords: *crises, long-term transformations, urban and territorial planning, uncertainty, public policy evaluation, pandemic, flooding, water management*

A crisis or an accumulation of crises? Which crisis(es)? For a long time now, the word has seemed empty, tired of being used to justify a widening gap between promises of development on the one hand and the stark reality that nothing is going according to plan. There is always a trigger for crises, a primary cause deemed paramount that causes events to fall (Walter Benjamin). It is a war that triggers an oil crisis, a speculative bubble that bursts, a virus that spreads, a storm that breaches a dyke and causes flooding… a shock that can be localised or global, with significant consequences in a circumscribed area or worldwide. However, this explanation of the root cause overlooks the regular waves of transformation that herald the rise of perils. The more perceptible signals of climate disruption and resource depletion are all warnings. The crisis, intended to be brutal and sharp, is then stretched out into a slow slump that feeds the comments of declinist experts and essayists.

Are we still in crisis? Or are we in the midst of a long and profound transformation that affects every aspect of our ordinary lives: our social ties, our relationship to the body and gender, and our historical, economic and geopolitical reading? So much for the social fact; our relationship to the planet, to territories, to ecosystems, to biodiversity and to life itself, for what concerns our relationship to the Earth.

This task invites contributions on the topic of Risk, namely on planning for adaptive capacity. For instance, proposals can deal with topics like the conditions and limits of planning, uncertainty in collective decisions and radical uncertainty, emergent crises like the recent pandemic, environmental disasters like flooding, etc.

Propositions are welcomed that shed light on theoretical principles, methodological approaches and empirical work. They can address, for instance, questions like: Given that we now face long-term transformations, how can we organise and pool our capacities to mitigate the consequences of our daily lives and adapt our practices? How can we even retain the ability to define common objectives instead of being tossed about like corks on the water? How can we express and prioritise, organise and adapt our systems (economic, institutional or social) to cope with the disaster, the evil that is coming (Pierre-Henri Castel), without abandoning the conditions of fulfilment, solidarity, freedom and transparency that forged our present. How can we express the problems that are already there or will be there in the future, perceptible in the long term and the context of diplomatic, economic and health uncertainties and threats? How can we finally take action on the ground? How can we define planning that will be useful in times of storm, i.e. capable of identifying our capacity to adapt? What diagnoses can we make, and what lessons can we learn? What tools can we use to overcome the uncertainties? Finally, is there a dimension required to carry out this planning?