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RESEARCH ARTICLE

Enhancing urban vitality: integrating traditional metrics with big data and socio-economic insights

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Abstract: A city is an intricate system where interactions between transport, land use, the environment, and the population occur at various scales. This complexity makes it challenging to predict and govern these interactions. However, big data on human activity patterns allows researchers to discover dynamic, temporary patterns in the activity landscape and understand the choreographies of people's behavior to enhance urban areas' vitality through planning. In this article, we hypothesized that a higher diversity of urban spatio-functional and socio-economic features indicates higher urban vitality in Tallinn, Estonia. We explored multi-sourced indexes to interpret this formation of urban vitality using complex agent variables of location, cluster, diversity, and similar actors generating self-organizing patterns of urban life. We used functional and morphological components and socio-economic data identified as traditional, 'slow' vitality measures (SM), and mobile phone location data as dynamic metrics (DM), respectively. We analyzed them in a geographic information system (GIS) environment to measure the types of spatial configurations, temporal variation of vital places, and their correlation. The results indicate a positive correlation (r= 0.5116) between the slow metrics and the high mobile phone activity. These correlations demonstrate that cell phone data provides a detailed and accurate view of people's daily rhythms and choreographies. The diversity indicators offer a new method to interpret urban vitality in cities and make planning decisions that support its emergence.

Keywords: urban vitality, spatial analytics, self-organization, human movement patterns, big data, mobile phone location

1 Introduction

Planetary urbanization signifies a global trend where more people live in cities, stressing the importance of strengthening positive urban qualities. Urban vitality is often considered a driving force of sustainability and a cornerstone in quality of life [27]. Recently, scholars in urban planning and design have been increasingly interested in understanding and promoting the vitality of cities [44]. Literature defines urban vitality as the life force and vibrancy of urban environments. It encompasses the dynamic and diverse activities, interactions, and flows within cities, reflecting their viability and capacity for urban progress [18, 55, 56]. Vitality is rooted in the idea that cities thrive when they create a sense of safety, vibrancy, and self-organized urban spaces for the people, fostering a rich street life and promoting varying visual qualities [42]. Urban vitality arises from intermingling different kinds of people and activities and contributes to the gradual evolution of land use [13, 22]. There is an urgent need to develop new strategies and planning methods to identify and support city features that contribute to urban vitality and sustainability.

Urban vitality is often associated with a high level of diversity: it suggests creating opportunities for random encounters and social interactions between people, enhancing economic growth and cultural enrichment, and generating economic prosperity and cultural diffusion essential for vivid urban life [13, 18, 54, 55]. As Vertovec [47] describes, a super-diverse population resulting from individuals arriving from many places leads to a highly diverse area with frequent random encounters. This broader understanding of diversity includes multiple intersecting factors like ethnicity, faith, immigration status, rights, gender, age, and spatial distribution [2, 47]. It helps identify place-making in super-diverse neighborhoods by reflecting the varied identities within these areas. It can be seen in the diverse range of people frequenting busy main streets, various facilities (such as retail and religious institutions), and in the clustering and networks of people rather than specific places [38]. Diversity is attractive because it draws more people, stimulates economic growth, and fosters a sense of belonging in cities.

Jane Jacobs, a renowned urbanist and pioneer advocate of urban vitality, emphasized the bottom-up evolution of urban space, the role of street life in this, and mixed-use developments to promote vitality in urban neighborhoods. In her view, urban vitality could be considered an emergent phenomenon resulting from the self-organization of various elements within a city that are difficult to create from the top down [13, 49]. This autonomous process leads to the formation of centralities and vital areas that unevenly appear throughout the urban fabric. These emergent dynamics have positive externalities, influencing the economic, cultural, and social aspects of urban life [23]. Studying urban vitality requires a comprehensive understanding of the mechanisms of the phenomenon and the underlying socio-spatial processes. It is essential to delve into the spatial and temporal dynamics and dependencies of human activities, their spatial implications [7], and complexities to recognize border conditions for encouraging the emergence of vitality.

Conceptually, urban vitality can be considered a form of self-organization: it emerges autonomously from the bottom-up from local interactions, where actors (both urban activities and human actors) make decisions regarding their location and mobility based on attraction to, for example, other similar actors, diverse environment, or high accessibility [4, 9, 13]. On the higher level of a neighborhood, city, or region, these individual decisions and plans appear as dynamic, spatial-functional configurations, patterns, and features, such as urban vitality. Here, we argue that although it is challenging to produce and control vitality from the top down, it is possible to enable it in urban planning by supporting existing and embryonic features associated with its autonomous emergence. We refer to these enabling features as indicators of urban vitality. To enable and foster vibrant cities, we must develop methods to guide and encourage urban progress favorable for vitality. Therefore, for appropriate policies and strategies, it is necessary to recognize and discover places with high levels or significant potential for urban vitality in the city, along with applicable indicators and measures for its recognition.

Urban vitality reflects the interaction between the spatial attributes of the city (such as configuration, density, and accessibility), the urban population and its flows, and the diversity of functions (such as types of activities, businesses, and services available) [51]. These interactions contribute to economic growth and co-presence variation, and we can trace the formulation of the functional-spatial vitality indicators to the pioneering work of Jacobs [13]. Jacobs's ideas have later been widely applied in city planning, for example, to access walkability [26], block size [28], point of interest (POI), and mixed-use [56]. These traditional metrics rely on infrequently collected, 'slow' data sets about population and cartographic representations, with a predominant emphasis on the physical/functional urban milieu. While often intuitively applied by urban designers, their efficacy in accurately capturing the intricate activity landscape, that is, the daily choreographies of people in the city, remains circumscribed. The traditional metrics exhibit limitations in fully capturing the dynamic and emergent nature of urban vitality. Notably, they somewhat overlook incorporating socio-spatial diversity indicators, constituting a crucial endeavor to foster inclusive urban environments. There is, hence, a need to 1) revise the applicability of traditional, slow metrics regarding how they reflect the activity landscape of a city and 2) introduce additional, dynamic measures that enable the validation of the traditional metrics and provide novel perspectives to the socio-spatial aspects of urban life.

In this article, we explored how diverse the physical and socio-economic components and the activity landscape of Tallinn, Estonia are. We also ask how these indicators correlate with the activity landscape observed through cellular data and which traditional indicators would apply as vitality measurements. Notably, we examined how high-frequency mobile phone data can realistically capture the multiple diversities in a city and ultimately assist in building applicable methodology serving spatial analysis that aims at long-term urban policies for complex cities. We used multi-sourced methods to minutely measure daily and hourly spatio-temporal variations of the urban activity landscape in Tallinn, Estonia. We applied mobile phone data from the Telia Eesti Telecommunications network and vitality indicators that embrace slower urban dynamic processes drawn from Jane Jacobs' conceptual, seminal work, along with socio-economic diversity components (income, age, gender, language, and education) to measure the formation of vital activity nodes and their diversity. In this study, we strategically prioritized specific aspects of diversity, aligning them appropriately with our research objectives, available resources, and the urban area under review. Then, we established a relationship between slow metrics and diversity indicators of mobile phone activity and compared hotspots.

2 Theory of urban vitality

The level of complexity in cities varies widely, making it challenging to fully understand or control the factors that contribute to urban vitality. While some cities or districts seem to function well, others struggle to create a vibrant and dynamic urban environment. This complexity underscores the need for a new, context-specific approach to understanding the factors promoting urban vitality [18].

The literature shows various factors affecting urban vitality. For example, the sense of safety in cities is instrumental to economic success and urban dynamics [42]. Overall, the literature suggests that good neighborhood vibrancy often requires dense population distribution, financial connectivity, and socio-economic diversity [12, 30, 33, 46]. Likewise, vital areas in the built environment require a dense concentration of people, buildings, and social activities [18]. Moreover, researchers have embraced the social and economic dimensions of urban spatial livability, such as diversity, affordability, and accessibility [33], because they attract spontaneous and voluntary interactions among individuals on all levels, generating pedestrian flows and intensive urban activities [50]. Consequently, urban vitality indicators typically concern diversities, accessibility/connectedness, and densities.

Vitality in the human environment emerges from the 'natural movement'—i.e., activity and usage patterns and pedestrian flows resulting from individual decision-making [52]. A certain degree of spontaneity is required to sustain the nature of cities as natural creators of diversity so that each urban community organizes itself around unique demands. Thus, different societies at different times have varying needs, underlining the uniqueness of cities and their identities, requiring new dynamic means capable of capturing this distinctiveness.

To comprehensively evaluate the potential vitality of present-day cities, the principles discussed by Jacobs need revision to incorporate novel insights, indicators, methods, and data reflective of vibrant urban life. Additionally, while many studies examine Jacobs' ideas in big cities or wealthy areas, there is limited evidence about vitality in cities advocating for sustainable urban dynamics.

2.1 Vitality as a self-organizing feature

Considering cities as complex adaptive systems (CAS), we understand urban vitality as an emergent feature resulting from dynamic interactions of human agents and activities—firms, organizations, associations, and institutions—within a city. Self-organization is a concept that refers to the capacity of a system to build order from its internal premises within the framework of restrictions but independent of external guidance [19]. Self-organizing dynamics and patterns are common in nature, from particles to biological and ecological systems. However, all CAS, including societies and cities, frequently adhere to the self-organization mechanism [34]. Economic clusters or cultural and social networks are prime examples [39]. Various factors drive self-organizing urban vitality from the bottom-up, such as actors choosing a preferable location, resulting in activity patterns, producing diverse dynamics and certain unevenly distributed economic and cultural landscapes [13, 49]. The emerging islands of higher urban vitality may influence the city or a region on a higher level, generating economic, cultural, and social advantages [23, 39].

With urban planning, the unpredictable nature of self-organizing dynamics requires a specific attitude, stressing the role of considerate maneuvers, enabling the intrinsic dynamics of the system and value-based, selectively prescriptive rules instead of strict control [1]. Consequently, we argue for the need to recognize and embrace a specific framework of measurable indicators applicable to planning and promoting urban vitality.

2.2 Indicators of urban vitality: traditional, slow metrics

Early studies defined the theory of urban vitality as the continuous presence, activities, and opportunities within an environment [31], the flow of pedestrians and active street life [35], and the safety and walkability of people around neighborhoods at different times [13]. These theories represent a sequential order for the life course of a city when urban vitality is decomposed into three components: urban morphology, urban function, and urban society [15]. We subsequently use the components to compute urban vitality utilizing fine-scale data.

In her definitive statement for urban vitality, The Death and Life of Great American Cities (1961), Jane Jacobs linked urban vitality to morphological diversity, understood as the city's built form and distribution of functions [44]. To establish a vibrant urban environment, she defined four conditions: (a) mixed land uses for activity, time, and space diversity, (b) small blocks and frequent street corners for contact among people, (c) age of buildings for coexistence, and (d) adequate urban density for high population and frequent encounters [13, 22, 36]. Jacobs' urban design principles have been widely accepted as effective despite lacking scientific validation [32]. However, recently, an increasing number of studies have scrutinized Jacobs' principles to evaluate contemporary cities across various disciplines, geographical areas, and research methodologies [5, 12, 56], emphasizing that a novel extended set of indicators is suggested to better reflect the current urbanity [10].

The static statistical data sources or traditional means of data collection—such as burdensome face-to-face interviews and field and questionnaire surveys, even when excluding spatial qualities [10, 31, 45]—offer an applicable framework for studying the overall vitality conditions in the city [18]. However, they overlook the dynamic, spatial flows of people essential for the concept of vitality, as Jacobs initially described, for example, in terms of vivid street life.

In this research, we observed that previous quantitative studies on vitality indicators often focus on variables related to various forms of diversity, density, and accessibility, revisiting what we call slow metrics. These studies offer a promising foundation for further evaluation. However, the integration of slow metrics with dynamic data, methods, and inclusiveness is still an emerging field and thus remains relatively limited. We aim to explore this research gap in-depth, enriching vitality studies with an emphasis on inclusion and deepening the understanding of urban vitality through dynamic indicators gathered via advanced methods and new (big) data.

2.3 New spatial data and urban vitality

Recent, swift progress in information and communication technology has enabled extensive data collection and, consequently, assessment of human activity intensity in urban space more precisely. These data provide increasingly convenient and accurate monitoring of human movement with extensive population coverage and high spatiotemporal granularity [17, 21]. In contrast, the principles of urban vitality—diversities, densities, and accessibility promoting human flows—have been retained as building blocks for vivid city life and can mostly be considered complementary methodology. The recently applied big data covers many location-based services (LBS) data sources, including social media data, public transportation smart-card data, taxi data, shared bike data, bank card transactions, and Wi-Fi access point data [21, 29, 48].

These data have been utilized as estimates of urban spatiotemporal vitality tracking in real-time, for example, human socioeconomic [3] and mobility behavior [8], and even to predict the dynamics of activity patterns at different times of the day using combined LBS data with traditional methods [24, 55]. Furthermore, geotagged mobile phone data has been used to depict the distribution of activity intensity in urban areas [37], along with crowdsourcing and location-based social media data to measure the intensity and variation of urban space [14,15,53], similar to transport smart cards [44].

Besides this growing and diverse array of digital data usage, mobile phone location data presents crucial opportunities to explore the social interactions, urban dynamics, and travel behavior of the population, thanks to the widespread penetration rate of the phones and carry-on usage [10]. Others have used it to, for example, validate neighborhood vitality with the number of accommodation check-ins [30], working day vitality [56], and night-time intensity of human activities and spatial variations [20,25].

This research often explores a single indicator for assessing urban vitality, which might pose challenges in comprehensively capturing the concept. Utilizing mobile phone data as observational data evades the constraint of relying solely on a single indicator and simultaneously mitigates the complexity of using multiple indices to depict urban vitality. However, the number of such studies is still limited. Moreover, various indices enable researchers to derive a relatively autonomous substitute value for urban vitality generated through external data sources. Here, we aim to fill this research gap, apply multiple vitality indicators, and combine slow and dynamic digital data in our exploration.

3 Data and methods

3.1 Study area

Our study area, Tallinn, is the capital of Estonia, the most extensive urbanized area, and the economic, innovation, and development engine of the country. The city was founded in the 13^{th} century and is currently a diverse blend of elements from medieval times to the soviet occupation regime and new liberal economy era, offering compact and green landscape features and historical monuments, e.g., the old town, a UNESCO world heritage site. The prosperity of modern industries and startups created abundant job opportunities for foreign people after the second independence of 1991. Tallinn covers an area of 159.3km^2, with eight city districts (see Figure 1), and had a population of 458,398 at the end of March 2023. Due to its wide range of built environment characteristics, Tallinn has an intrinsically high level of morphological and functional diversity, making it a prime case for the study of urban vitality presented in this article.

The soviet occupation (1940-1991) heavily influenced the demographic, linguistic, and architectural landscape of the city. Preliminary from the 1960s, large-scale 5-10 stories housing projects were built in the new suburbs, such as those in Mustamäe and Lasnamäe, to accommodate the growing population, including the remarkable Russian immigrant population (currently nearly 50% of the population are Russian speakers). These districts have good transport to the city center [16] and a remarkably high population density. Today, these districts divide the physical activities of the city into fragmented public spaces of community neighborhoods for people to live, socialize, shop, and work; variation in population density amongst the districts somewhat influences the social areas.

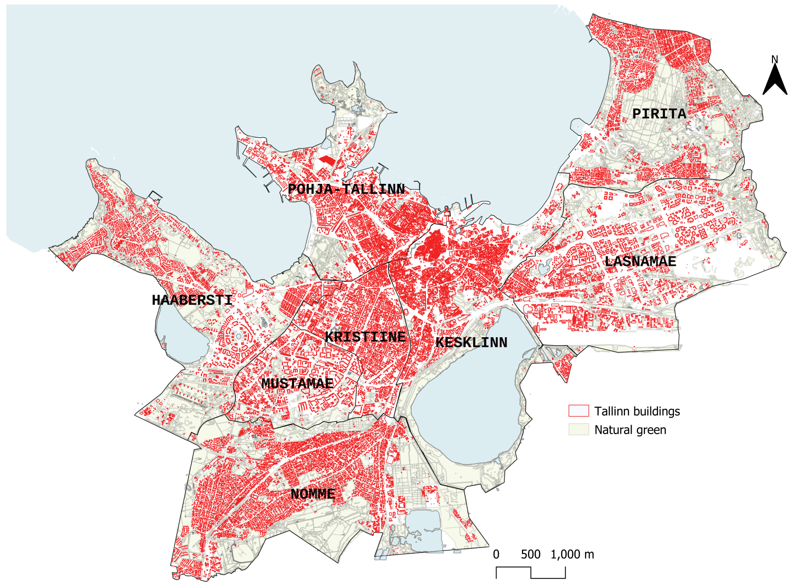

Figure 1: The study area shows Tallinn's eight city districts.

3.2 Data sources and processing

In this study, we applied data about urban morphology (ages and uses of buildings along with street networks), functional data (population, socio-economic variables), and human mobility (the locations of people by cellphone data per hour for months) for Tallinn. We applied Jacobs' fundamental concept of the presence of people to examine population density. Then, we examine the emphasis on the necessity of a blend of primary uses assessed through land use mix as the uses of buildings. The contact opportunity is evaluated primarily through a block size, implying that higher frequency for encounters correlates with smaller blocks. Out of many indicators for interaction, we hence use street networks to measure intersection/street corner density. After that, the need for aged buildings is examined by analyzing the year of building construction. Lastly, we assessed urban vitality by analyzing various demographics using socioeconomic data. The selected data set unit of measurement is in a spatial resolution of 250m x 250m for the slow vitality measures (SM) and 500m x 500m for dynamic metrics (DM). We define SM as traditional urban vitality components and DM as the spatial data from mobile phones.

The data types and sources in Table 1, made it possible to study spatiotemporal variations in the flow of people at a low granularity scale and explore how these variables affect multiple diversity indices. We compared the mobile phone activity dataset of 2020 and 2021 to determine which resources are more suitable for our analyses and concluded with 2020[1]. Finally, we complemented the grid-level statistics with mobile phone data reflecting

[1]We carefully scrutinized the available data taking into account the COVID-19 pandemic ongoing at the time of data gathering. We selected the time sets that reflected periods of low infection rate and relaxed restrictions and validated them by comparing the data patterns with the 'normal year, in this case, 2021', hence the choice for the 2020 dataset.

the dynamics of human activities within the study area during the summer of July and autumn of October.

Indicators	Variable	Data source	Year	Grid size
Socio-economic characteristics	Age, Income, Education, Language, Gender	Statistics Estonia	2020	250m
	Urban density (population)	Statistics Estonia	2020	250m
Jane Jacobs's metrics	Building (mixed-uses & aged buildings)	Estonia building register (open-source)	2022	250m
	Road network and district boundaries	Tallinn geoportal spatial data (open source)	2021	-
Activity data	Mobile phone records (daily, hourly, monthly)	Telia Eesti telecommunications company	July & October 2020	500m(-4000m)^2

Table 1: Data types and sources.

3.3 Data preprocessing

3.3.1 Mobile phone data

We used mobile phone location data from the largest telecommunication provider in Estonia, Telia Eesti, which serves 40% of the market population, to assess urban vitality by representing the total population of mobile phone users, with a 97% smartphone penetration rate as of 2023. Unlike call detail records (CDRs), which only capture a person's location during communication activity (such as a phone call or text message), our dataset provides real-time data on distribution, density, and human activity dynamics in different areas. Figure 2 shows data from Telia Eesti, recording the 24-hour daily activity of mobile phones in cells at hourly intervals from 2020 to 2022. It captured instances where people were stationary in a given location for more than 20 minutes.

The aggregated monthly data includes counts of daily visitors (both residents and visitors from outside Tallinn) and sums multiple trips by a single device within the same cell, allowing for multiple counts of a subscriber within a day and recounting if they appeared in another cell. Each anonymized data entry contained the date of record, the hour in the local time zone, the unique identifier of each cell, the name of the cell, the municipality name, the size of the cell in meters, the rating of data quality (A=high, C= Low), and population in each cell (see Table 2). It is important to note that the dataset does not identify meaningful places such as home and work locations for these users. Finally, for more granularity, we selected the 500x500 meter cell size data in July 2020 and October 2020 to reflect hourly intervals from 0:00 to 23:00 on weekdays (Monday-Friday) and weekends (Saturday and Sunday). The cell size (500m) reflects approximately a five-minute walking distance. The selected dataset covered the entire working month (October 1-31, 2020) and the summer holiday month (July 1-31, 2020).

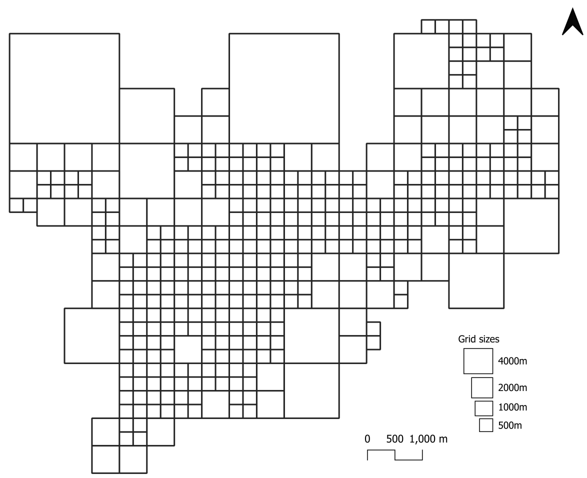

Figure 2: The grid-based clustering of mobile phone users in Tallinn. Cell sizes vary according to the frequency of traffic, ranging from the most frequent (500m) to the least frequent (4000m). The entire time series covers most inner-city areas with 500m cells.

Batch_ Date	**Local_ Hour**	**Area_ Code**	**Cell_ name**	**Admin_ Level_2**	**Grid_ size**	**Cvi_ Rating**	**People**
01/02/2020	0	110	Kakumäe	Tallinn	4 000	A	31
01/11/2020	0	113	Vene-Balti sadama	Tallinn	2 000	A	306
01/04/2021	23	120	Kauai Cafe	Tallinn	1 000	C	490
19/04/2022	18	319	Sossimägi	Tallinn	500	A	2295

Table 2: A sample of Telia's daily mobile phone records.

3.3.2 Socio-economic data

Socio-economic datasets for 2020 contained ten demographic indicators aggregated in the national standard spatial resolution of 250m x 250m square grid (1411 cells) by Statistics Estonia. The database covers sensitive socio-economic, cultural, marital, and geographical information of residents living and registered in Tallinn. In addition, the data provider ensured data privacy by identifying and removing data for cells with fewer than five people, which resulted in some cells being left redundant. For this research, we explored the influence of five demographic variables: age, income, education, language, and gender. These elements constitute the foundation of urban life, forming diverse combinations that profoundly impact urban vitality and economic growth. The variables reflect the population, built environment, and job structure in each cell.

3.3.3 Data for traditional, slow vitality metrics

Regarding the traditional, slow vitality indicators, we obtained data from the open-access platform of the Estonia building register (https://livekluster.ehr.ee/ui/ehr/v1). We manually cleaned data on the Estonia building indicators and conditions (planned, existing, when erecting, and unrealized). The buildings with the condition of 'when erecting' and 'existing' were selected because they represent the current urban built forms constructed from 1250 to 2022. We generated point data of 62,553 buildings and aggregated them into polygons for further analysis. The statistical population represents the urban density data. We analyzed street corner density from the street length extracted from the road network of Tallinn's base map data (https://www.tallinn.ee/et/geoportaal/ruumiandmed).

4 Analyses

4.1 Measuring diversity using traditional data variables

To better understand the link between urban diversity and vitality, we investigated the spatiotemporal changes in human movement. We evaluated the vitality of areas in Tallinn using the four morphological attributes of the built environment (density of uses and people, building ages, and street corner frequency). We combined these attributes with other traditional datasets to obtain a reliable measure of urban diversity.

To successfully combine these multiple diversity indices, we employed two different entropy metrics. We compared the Shannon Entropy Diversity Index (*H*) results with the Simpson's Index of Diversity (*S*). Shannon entropy measures the extent of mix or evenness in the distribution of land use types, making it more sensitive to the presence of rare types [56]. In contrast, the Gini-Simpson (1 – Simpson's original index) emphasizes dominance and is more sensitive to the most common land use types [40].

The background of Shannon's measure in the information theory [41] gives it a statistical character that allows for measuring the degree of spatial concentration or homogeneity of a built-up area among 'n' spatial units [6]. The Shannon entropy is expressed as:

$$H = -\sum_{i=1}^{n} P_i ln P_i \tag{1}$$

Where H expresses diversity in terms of Shannon information entropy, P_i is the proportion of the variable in the ith zone (cell), and n is the total number of traditional metrics in the cell. The entropy value ranges from 0 to $ln(n)$, where $ln(n)$ is the maximum entropy limit. Similar to the metrics of urban sprawl, where a higher H value of the entropy indicates greater urban sprawl [43], we represented cells with lower traditional metrics indicators as less diverse and cells with higher traditional metrics indicators as more diverse. Simpson is calculated as:

$$S = 1 - \sum_{i=1}^{n} {P_i}^2 \tag{2}$$

Where S is the diversity index of species (indicators), P_i is the proportional abundance of species i calculated as (n_i/N), (n_i) is the number of one particular species found divided by the total number of individuals (N), Σ is the sum of the squared proportional abundance and n is the number of species. Simpson's values range from 0 to 1; the greater the value, the greater the sample diversity. Using this method, we observe that vitality rises when there is a high mix of land use functions, various building ages, street intersections, population, and socioeconomic groups in a cell. Therefore, we calculated the indicator of each Shannon diversity index, standardized the sum of the variables, and performed descriptive statistics (Table 3).

Variables	N	Indicators	Mean	Med.	SD	Min	Max
Socio-economic factors	1408	Age, Gender, Education, Income, Language	0.579	0.616	0.375	0	1
Mixed land-uses	1744	Residential, Accommodation, Office buildings, Trade & Services, Other buildings	0.559	0.608	0.197	0	1
Urban density	1408	Population	0.145	0.094	0.165	0	1
Street intersection	1744	Road intersection density	0.173	0.118	0.163	0	1

Table 3: Variables and descriptive statistics of shannon entropy.

4.2 Activity patterns of mobile phone users

Next, we analyzed the hourly activity pattern of mobile phone users in Tallinn on weekdays (Mondays-Fridays) and weekends (Saturdays and Sundays) during July and October 2020. The activity landscape per cell, measured in one-hour intervals, varied with a minimum of 600,000 mobile activities across 346 cells, each 500m by 500m. Since the mobile phone record did not include trip or home location information, home-based trips were not distinguished.

We aggregated the two-month data and derived descriptive statistics (Table 4) to recognize the activity flow. Then, using natural breaks in geographical information software (QGIS), we classified the temporal spark of each cluster as low, medium, high, very high, and extremely high activity.

	2020	Mean	Median	SD	Mini	Max
July	weekday	24931893	25074970	697091	23910956	26652338
	weekend	8512518	8627124	502950	7730371	9463288
October	weekday	10302977	10422144	309124	9808848	10746176
	weekend	3463484	3480495	94505	3314738	3694737

Table 4: Activity landscape metrics descriptive statistics.

We also categorized the temporal characteristics of the mobile phone activity to assess flow or activity changes into four time periods: Midnight (0:00–6:00), Morning (6:00–12:00), Afternoon (12:00–18:00), and Night hours (18:00–24:00).

In Table 5, we selected and compared the percentage using natural breaks of very high and high cells of the traditional indicators in the Shannon entropy values with the very high cells of activity landscape to see the spatial relationship and the hotspots of cellphone activity.

4.3 Correlation between traditional and new metrics

We produced a unified spatial layer for the correlation analysis of SM and DM variables. We used the processing tools in QGIS to divide one of the grid layers (500m) with the other geometrics (250m) using intersection and spatial join to get all values from the correct locations into the same layer.

Then, with the data combined from both original layers in one single layer, we standardized the data in Microsoft Excel (standardize function) to normalize values (z-score)

[h]

Indicators	High & Very high cells	Total cells	Percentage
Socio-economic	696	1408	49%
Mixed landuse	585	1744	34%
Street intersection	441	1744	25%
Urban density	200	1408	14%
	Very high cells		
July weekdays	71	346	21%
July weekends	84	346	24%
October weekdays	67	346	19%
October weekends	72	346	21%

Table 5: Spatial relationship of SM and DM by percentage.

and eliminate differences between the variables from different scales. Afterward, we ran the Pearson correlation to find where the correlation is high and low (Figure 7) and determine which correlations are statistically significant. Finally, we performed a regression analysis (Table 6).

R	R^2	P-value	DF
0.5116	0.2618	0	1

Table 6: Presents the result of the correlation analysis, showing a positive correlation between cell phone activity and socio-economic variables.

5 Results

5.1 Spatial distribution with traditional vitality metrics

5.1.1 Diversity in slow metrics

Figure 3 illustrates the diversity of SM in Tallinn's physical components. The *age of buildings* showed a prevailing landscape of diverse years of building construction classified as pre-modernism (< 1920) to recent years (2001-2022). The north, central, and south areas of Tallinn, along with the harbor, have diverse concentrations of buildings from the soviet peak period (1961-1990), early democracy (1991-2000), and recent buildings (2001-2022). Buildings located in the northeast and northwest showed a low diversity of structures from pre-modernism, the first independence time (1921-1940), and the soviet occupation time (1941-1960), indicating a predominance of residential buildings and the presence of modern subdistrict shopping centers in these areas.

The *mixed-use buildings* also followed the diversity pattern of the age of buildings, with the center of the Tallinn map showing more medium diversity, while the cells around the edges indicated lower diversity. The result shows the sparse distribution of building use classifications (12 categories) in high economic zones (e.g., catering buildings, entertainment, public buildings, etc.). In contrast, cells dominated by monofunctional services—such as office buildings, industrial areas, transportation, residential, and service buildings—presented very low diversity because of their land use function. The five categorized variables for the mixed uses resulted in a maximum entropy value of 1.714, indicating higher diversity.

The *urban density* dataset (see Figure 4) shows that cells with moderate, high, and very high diversity were clustered around tourism destinations, high-rise residential areas, and Tallinn city center. In contrast, surrounding areas demonstrated very low urban density, particularly single-family houses, and monofunctional service areas. The maximum entropy value of 0.032 reflects a lower urban density mixture among different cells.

The *street intersection* displayed very low density values (1-10) in the north, central, and south parts of the city, but a higher concentration of low (10-20), moderate (20-30), high (30-40) and, very high (40-50) density values in areas with diverse building ages and mixed-use buildings. Locations with extremely high vitality values (50-60) were primarily in high-active regions—for example, areas around social spaces, historical centers, and commercial areas. We calculated the street intersection entropy as 0.018 and a minimum walking distance between 1 and 2km.

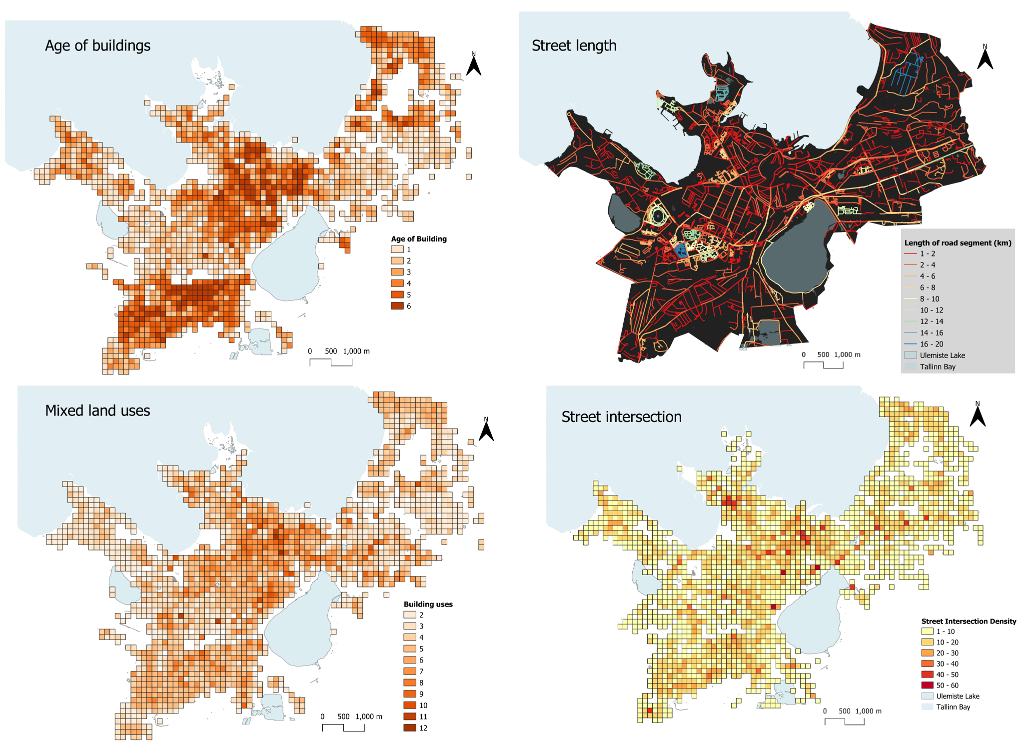

Figure 3: The physical components of Tallinn show the SM variables: the year of construction as the age of buildings, mixed-use buildings as mixed land uses, and street intersection measured as street length and density.

5.1.2 Diversity of the socio-economic metrics

Figure 4 illustrates the socio-economic diversity variables, which indicated a heterogeneous pattern of moderate, high, and very high diversity across the south, north, east, and center areas. It included various locations such as businesses, administration, central residence districts, and essential life service facilities.

We used the indicators (age, language, income, gender, education) to assess the presence of various social demographic places across the city. The findings revealed a homogeneous spatial distribution for age, education, and gender. In contrast, there was a cluster of language diversity in the center area, where they speak three languages (Estonia, Russian, and others). In comparison, only two languages are predominant in other areas, particularly in the north, south, and west. Also, we used Shannon Entropy to calculate multiple diversity indicators across all SM. We selected higher diversity values of the sum of the maximum values for all socio-economic indicators (age, gender, education, income, and language), which totaled 6.375. It confirms that higher diversity values in a cell reflect higher overall diversity.

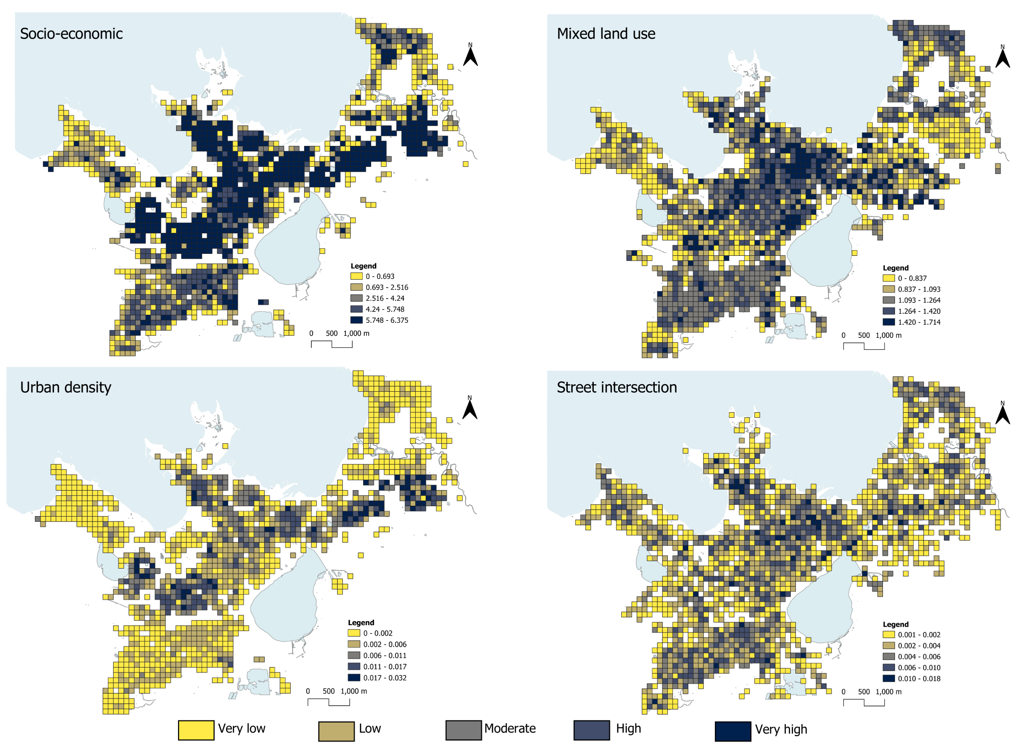

Figure 4: Shannon entropy diversity values for socio-economic, mixed-land use, urban density, and street intersection.

5.1.3 The diversity hotspot

Shannon diversity measures the richness of traditional metrics in each cell but does not account for their abundance. We showed the dominance of these variables using Simpson's diversity index (1-D), which ranges from 0 to 1, where 0 signifies the absence of diversity (i.e., maximum homogeneity) and 1 indicates maximum heterogeneity (i.e., diversity). Table 7 illustrates the dominant diversity variables of the traditional data, and we standardized the sum of the socioeconomic indicators and mixed land uses to maintain the low and high diversity principle.

According to the guidelines for interpreting the Simpson diversity index score [11] in Figure 5, most of the cells illustrated a high diversity of socio-economic variables, with diversity scores ranging from 0.81 to 0.99. At the same time, the central cells maintained absolute heterogeneity. Scores indicating moderately high diversity of mixed land uses ranged from 0.61 to 0.81, demonstrating the diversity throughout the city. Additionally, urban density revealed a high homogeneity between 0 and 0.01 and a low diversity index score of 0.01 to 0.41, while the street intersections showed no diversity in any cells.

Therefore, comparing the diversity values of the Shannon and Simpson indices for the socio-economic variables suggested that the cells were highly diverse, characterized by a high number of variables with minimal dominance by any single variable. Conversely, mixed land use showed a high Shannon diversity score and moderately high Simpson score, indicating no single variable overwhelmingly dominating within any cell. On the other hand, urban density revealed a single dominating variable and no single variable dominating cells, while the street intersections exhibited extremely low diversity, as only one variable was represented.

Simpson's index of diversity					
Variables	**N**	**S.D**	**Mean**	**Min**	**Max**
Socio-economic	1408	0.317	0.719	0	1
Mixed-land use	1744	0.147	0.275	0	1
Street intersection	1510	0	1	1	1
Urban density	1419	0	1	1	1

Table 7: Shows the descriptive statistics of the dominant traditional diversity variables in a cell, where 0 indicates low diversity, and 1 indicates high diversity.

5.2 Activity patterns in mobile phone data

Figure 6 illustrates a significant variance in the activity landscape within the city over time. Cells with very high cellphone usage were clustered around the most central urban areas in the city center and subdistricts, influenced by the diversity of uses. Cellphone activity varied across different days and times, as detected on the weekdays of July. We observed very high activity at 03:00, high at 08:00, medium at 17:00, and low activity between 20:00 and 23:00. This pattern reflects peak work hours, shopping times, and sleep periods. The variations between weekdays and weekends also contribute to the unpredictable nature of human activity. On July weekdays, high activity was concentrated in commercial and business centers in the central region, while on weekends, they mainly focused on commercial and high residential areas (homes). Activities were very high at 02:00, medium activity at

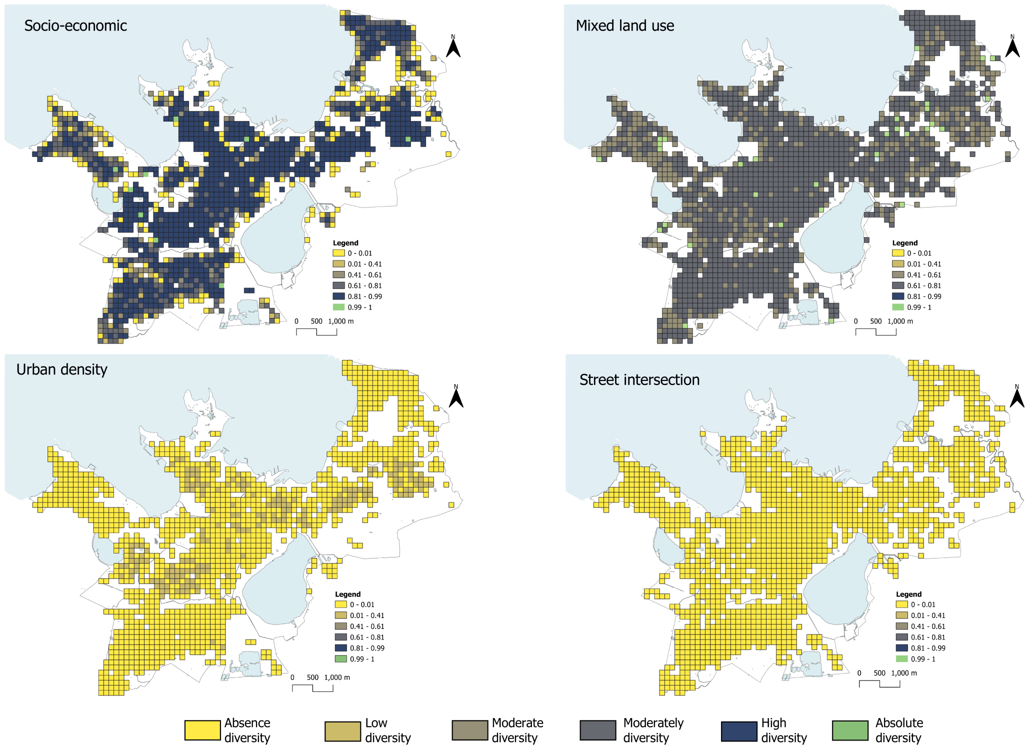

Figure 5: Simpson diversity index values for all the traditional metrics.

05:00-10:00, low between 12:00-17:00, and high between 18:00-23:00. It was surprising that very high activity was observed during sleep time at 02:00 and 03:00 for weekends and weekdays.

Consequently, the October data showed a decrease in cell phone activity but no significant difference in geographical hotspot areas compared to the July activity result. A downward movement from 04:00-09:00 (sleep time) remained very low between 10:00-16:00 (family time) and increased again from 17:00-23:00 (social time). It demonstrated that activity between 06:00-12:00 on weekends was low, while it disclosed a fluctuation trend on weekdays. Between 18:00-23:00, weekends presented a high upward trend, and weekdays showed a downward trend. Overall, the changes in urban vibrancy on weekdays and weekends in July and October were not synchronous.

Nonetheless, there was a very high level of cell phone activity on July weekends and October weekdays, while unstable activity was high and low on July weekdays and October weekends. An interesting but not unexpected finding was that urban life is higher in summer than in winter in large-scale residential areas, urban density areas, and mixed land type areas, which correspond to our assumptions.

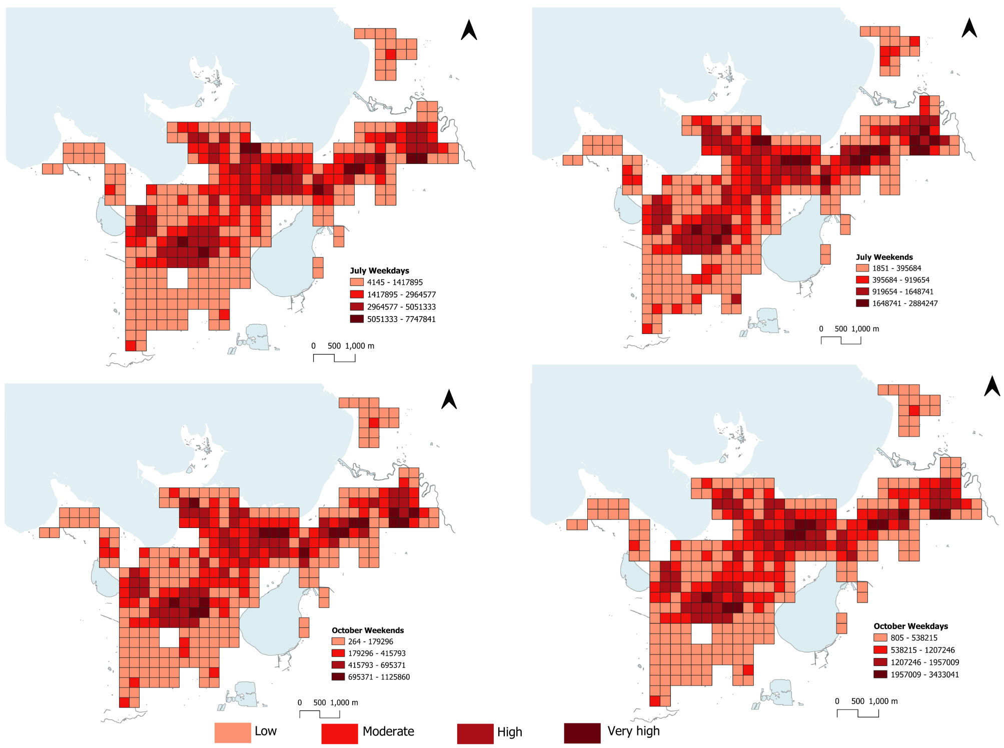

Figure 6: We used natural breaks to group similar values and maximize class differences for the July and October activity patterns.

5.3 The relationship between traditional and new metrics

The correlation results for the standardized SM and DM data of the independent variable (socio-economic) and the dependent variable (cellphone), as presented in Figure 7, revealed that the socio-economic variables significantly correlate and influence the vitality value in each cell.

These results demonstrate a positive spatial correlation of all variables in space, especially between zones we classify as low, medium, and high vitality in Figure 8. The low urban vitality areas characterize the suburban areas outside the urban center of the city. At the same time, an even distribution of low urban vital areas surrounds zones of medium diversity and regions exhibiting high vitality levels. The concentration of high agglomerations in central areas reveals a high urban vitality level.

6 Discussion

First, the results showed that traditional urban vitality indicators—such as diverse land use, a densely populated and built urban environment, and accessibility via a dense street network—strongly correlated with high vibrancy as measured by cellphone activity. This

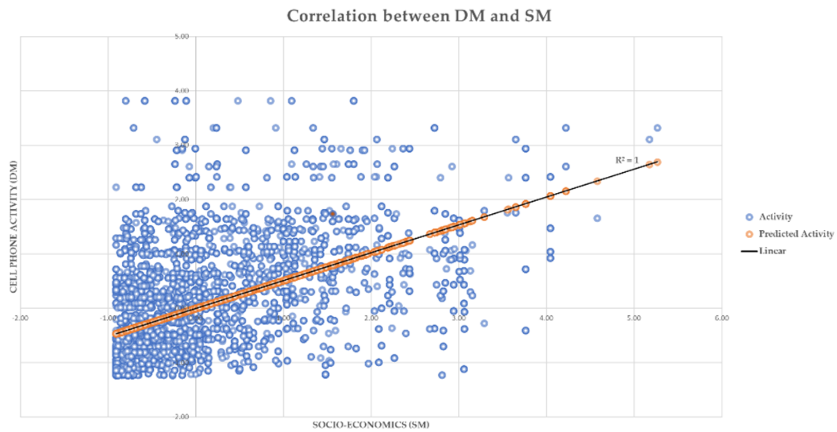

Figure 7: We used the z-score in each row (cell) to analyze the correlation between dynamic and slow metrics.

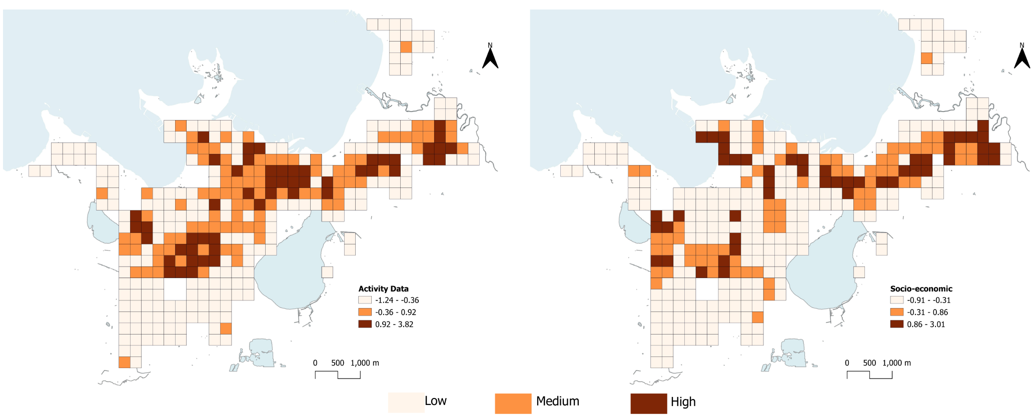

Figure 8: Spatial correlation between cellphone activity data (left) and socio-economic metrics (right).

vibrancy was concentrated in the city center and other spatially centralized locations. The co-occurrence of these indicators suggested that they could serve as valuable tools in urban planning and governance, allowing for assessing vitality levels in specific areas or creating a vitality landscape for the entire urban region. These metrics could be utilized to identify and enhance vibrant city areas. Moreover, identifying neighborhoods with solid potential for vibrancy, characterized by a desirable combination of these vitality indicators, could strategically support and promote the self-organizing development of vitality from the bottom-up while maintaining their unique local identities, which rigid, uniform top-down interventions might otherwise undermine.

Secondly, comparing socio-economic factors—such as income, gender, education, language, and age—and the traditional urban vitality indicators revealed co-location patterns emphasizing the interaction between diverse income levels, high urban density, and mixed land uses. These patterns were predominantly observed in areas with high mobile phone usage during daily activities. Given the complexity and self-organizing nature of urban processes, it isn't easy to establish a clear causal relationship between income, mixed-use, and density. However, in line with Jane Jacobs' observations, we argued that random encounters among diverse groups of people are more frequent in areas with mixed activities and dense urban fabric. This setup could help to prevent the concentration of homogeneous populations, reducing segregation and the formation of enclaves like gated communities. For Jacobs, such encounters fostered a sense of safety and innovation, both of which contribute to the vibrancy of cities.

The distribution of socio-economic concentrations across Tallinn appeared relatively uniform, except for income, which may be more sensitive to spatial patterns associated with spatially uneven land prices. While the methodologies applied did not reveal significant socio-economic differences overall, future research advancements may shed light on these variations. Additionally, the potential impact of planning decisions affecting mixed-use areas, income, and density in central locations is plausible. However, these factors are relatively new to the planning strategies of Tallinn and are yet to be reflected in the urban landscape. The future effects of such strategies require further investigation.

Thirdly, an analysis of the temporal patterns of human movement revealed that the relationship between all indicators—both traditional and socio-economic—and the cellphone activity landscape generally indicated higher levels of vitality in daily spaces and during peak hours. We observed significant fluctuations forming patterns that vary by hour, day, and season. Concentrated spatial rhythms emerged in various areas: popular entertainment destinations such as nightlife clusters in the old town, high-rise residential areas like Lasnamäe reflecting work-recovery cycles, and historic areas, with noticeable pulses of tourist activity in old town due to the frequent connections to Helsinki and Stockholm at the harbor. Additionally, we observed dynamic patterns in active social spaces, such as Telliskivi, a mixed-use area with workspaces, cafes, event venues, housing, commercial districts, and malls. These temporal variations were evident on both weekdays and weekends, though with slight differences in timing.

Furthermore, activity patterns varied significantly between a typical working month (observed in October) and a typical holiday month (July), reflecting the high concentration of people at different hours throughout the city. While both seasons maintained peak and rush hour activity, the overall population activity increased in the summer, mainly due to tourists. The movement of visitors and residents across different locations in Tallinn contributed to an uneven and seemingly random activity distribution. It suggested that beyond routine daily activities, the summer activity landscape becomes more concentrated in areas with distinctive attractions, diverse activity types, and specific physical environments, such as Tallinn town hall square and Telliskivi creative city. These findings highlighted that when aggregated into a yearly average, the temporal landscape of activity conceals a more complex and fluctuating pattern. The analysis, incorporating both long-term averages and seasonal variations, offers valuable insights for urban planning. It underscores that the activity landscape, much like urban vitality itself, is a self-organizing phenomenon characterized by emergent patterns that may be difficult to predict. Therefore, a multimethodological approach, utilizing diverse data sources as employed in this study, is essential for a comprehensive understanding of these dynamics.

Our findings were consistent with the conditions for urban vitality outlined by Gomez-Varo et al. (2022), demonstrating that in contemporary cities, urban vitality is not solely determined by income levels or specific urban fabric features but rather by a combination of certain urban characteristics. It also complements and extends the interpretation of Jane Jacobs' concept of vitality, defined through empirical observation but not fully quantified. Our metrics captured the variations in flow patterns strongly associated with urban vitality, thereby providing a means to quantify the quality of urban spaces. By measuring the diversity and vitality of human movements and their presence in urban places, we offer accurate quantitative metrics for these phenomena. Also, integrating socio-economic and mobile phone data enhances urban planning and policy decisions by providing a complementary perspective on the spatiotemporal patterns of urban vitality at hourly, daily, and weekly intervals, highlighting the everyday use of physical spaces across different spatial units.

6.1 Limitations

Dynamic data from mobile phones is crucial for understanding fluctuating human activity patterns, the emergence of urban vitality, and the broader complexities of city dynamics. While our multimethodological approach, grounded in spatial analytics, offers a robust framework for assessing the urban activity landscape and vitality metrics, it is essential to acknowledge certain limitations that persist. These include potential biases in data representativeness, challenges in capturing long-term patterns, and the need for further refinement of the metrics to address diverse urban contexts comprehensively.

Firstly, the data collection and aggregation methods of the data provider create many limitations. The absence of detailed information regarding the purpose of trips hinders our ability to accurately interpret changes in activity patterns. Likewise, discrepancies in the spatial resolution between the mobile phone data and socio-economic datasets make it challenging to align the two sources. However, we can mitigate these uncertainties from unequal cell sizes by utilizing intersection and spatial join techniques, which ensure uniformity in cell sizes across both datasets for more precise analysis.

Secondly, the inherent behavior of mobile signals in selecting the nearest mast adds uncertainty about the exact location of the phone. For instance, unusually high activity recorded at 03:00 on weekends likely reflects a data collection anomaly rather than actual behavior.

Thirdly, the spatial analytics method used to compare high-value cell percentages and establish relationships between traditional indicators and mobile phone activity produces coarse results. A more refined approach could be implemented to investigate these spatial relationships in greater depth. Future research should address these challenges by refining data collection methodologies and utilizing GPS data when available. Such improvements are essential for enhancing the accuracy of urban dynamic analyses and advancing the field of urban studies.

Finally, to fully capture the richness of the socio-economic landscape, a more diverse set of indicators could have been used in addition to those available for this study. Factors such as occupational prestige, race, religion, home ownership, and family size would provide a more comprehensive image of the diversities and dependencies of the city. As a result, some nuances in the correlations between these diversities may have gone unnoticed and could be revealed through further research using a wider range of socioeconomic factors.

7 Conclusions

In this study, we investigated the applicability of traditional, i.e., functional and morphological, indicators of urban vitality as measures of city vibrancy in Tallinn, Estonia. Additionally, we used cellphone activity data alongside socio-economic, statistical, and spatial variables to examine the correlation between these indicators and the dynamic activity landscape. This approach allowed for a comprehensive analysis of the relationship between urban form and function and the patterns of human activity, providing insights into the factors that contribute to urban vibrancy.

We demonstrated that traditional metrics, including land-use diversity, built fabric density, activity levels, and street intersections, are reliable proxies for urban vibrancy, corroborating existing literature highlighting their role in fostering socio-spatial interactions. Our analysis of socio-economic metrics revealed a significant correlation between income diversity, mixed activities, and urban density. It likely indicates that diverse urban hubs attract a wide range of people, influenced by rental rates and land prices while facilitating interactions that enhance urban life. These diverse hubs contribute to the viability and safety of streets, reinforcing their importance in maintaining vibrant urban spaces.

In addition, we mapped significant fluctuations in the activity landscape, capturing the daily, weekly, and yearly patterns of human movement. These findings emphasize the need to comprehend the dynamic, transient, self-organizing, and often unpredictable nature of urban environments. Understanding these temporal variations is critical for effective urban planning, as it requires specialized attention to the evolving rhythms of city life. It, in turn, calls for adopting appropriate methodologies and data-driven approaches to guide the governance and design of urban spaces in a manner that aligns with their inherent complexity.

Our study addresses a significant research gap by introducing multimethodological approaches and metrics for assessing urban diversity and vitality, facilitating the observation of flow pattern variations closely linked to urban vibrancy. By integrating socio-economic data with mobile phone activity data, we provide a novel and complementary perspective on the dynamics of urban vitality. This approach enriches urban planning and policymaking, extending and refining early frameworks in vitality studies and offering more profound insights into the spatiotemporal patterns that shape vibrant urban environments.

We propose that future research could extend the application of our method to analyze urban vitality in other cities and regions, given its potential to capture the distinctive features of different urban environments. This approach offers a valuable tool for devising localized strategies to enhance urban vitality, allowing for tailored interventions that address the specific needs and characteristics of each urban area. By adapting the method to diverse contexts, urban planners and policymakers could better foster sustainable, vibrant city spaces that respond to the unique socio-spatial dynamics of different localities.

Besides, future research could scrutinize local variations by integrating qualitative methods for triangulation. It would involve capturing individuals' subjective experiences to classify neighborhood areas based on their distinct identities. Such an approach would offer deeper insights into social fabric and lived experiences in urban spaces. Furthermore, refining the accessibility analysis by incorporating measures of centrality or other network characteristics could yield a more nuanced understanding of accessibility dynamics, offering a comprehensive perspective on how urban networks shape mobility and interaction within cities.

Our findings offer substantial implications for policymakers, developers, and urban planners, providing them with critical insights and tools to develop strategies, policies, and practices rooted in a comprehensive understanding of urban dynamics. By fostering the emergence of vitality through targeted support for diverse land uses, population densities, frequent street networks, and mixed-use developments, planners could cultivate the vibrancy that is essential to urban life. These policies should prioritize the attraction and empowerment of local stakeholders, facilitating a bottom-up approach to urban development rather than relying solely on top-down strategies or master plans. It would promote social cohesion and economic resilience and encourage adaptive reuse of existing buildings, contributing to sustainable urban growth management.

Interestingly, the foundational principles of diversities and densities, introduced over six decades ago by pioneering urbanist Jane Jacobs, remain integral to fostering urban vitality, even in today's digital and virtual landscape. Jacobs' insights into the interdependence of mixed uses, population density, and active public spaces continue to serve as critical building blocks for dynamic cities. Urban planners can make more informed decisions by revisiting and reinforcing these ideas with contemporary data and advanced methodologies. This enhanced understanding allows for the more strategic allocation of resources and informed modifications to land-use policies, ensuring that cities remain vibrant, active, and resilient in physical and digital contexts.

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