

Digital behavior spatial model: Integrating Takunai and Google Maps API for behavioral-based urban space analysis in the Kupang Waterfront Area, Indonesia

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ARTICLE INFO	ABSTRACT
<i>Article history:</i> Received June 25, 2026 Received in revised form July 24, 2026 Accepted August 19, 2026 Available online September 01, 2026 <i>Keywords:</i> Digital behavior Spatial Model Digital urbanism Google Maps API Smart city Spatial behavior Urban analytics *Corresponding author: Donatus Ara Kian Doctoral Study Program in Digital Architecture, Faculty of Architecture and Design, Universitas Katolik Soegijapranata, Indonesia Email: donarakian@unwira.ac.id	<i>The rapid expansion of urbanization, accompanied by the growing implementation of smart city initiatives, has generated an increasing demand for data-driven approaches capable of documenting and interpreting actual human behavior within urban environments. Conventional techniques for behavioral observation, including questionnaire-based surveys and manual behavioral mapping, frequently encounter limitations associated with temporal coverage, scalability, continuity of observation, and potential observer bias. In response to these challenges, this study proposes a Digital Behavior Spatial Model (DBSM) that integrates Takunai, a mobile-based spatial-temporal tracking application, with Google Maps API to reconstruct urban spatial configurations from behavioral traces generated through real-world human activities. The research was undertaken in the Kupang Bay waterfront area, Indonesia, using GPS trajectories, timestamps, visitation frequencies, movement paths, and location-based service data collected throughout a fourteen-day observation period. A combination of spatial-temporal analysis, density mapping, activity-node extraction, movement-corridor analysis, and spatial-network analysis was employed to identify recurring patterns of urban activity and movement. The findings demonstrate the emergence of multiple activity nodes, dominant movement corridors, and a semi-polycentric spatial configuration characterized by strong recreational-commercial interactions along the waterfront. Pronounced temporal variations were also identified, demonstrating a process of spatial reorganization between daytime economic activities and nighttime recreational and social functions. These findings indicate that urban space is dynamically produced through collective behavioral interactions rather than being determined exclusively by formal planning regulations and predetermined spatial classifications. The proposed DBSM contributes theoretically to the fields of Digital Urbanism and Complex Adaptive Systems while providing practical implications for smart city development, continuous urban monitoring, evidence-based urban design, digital urban governance, and adaptive spatial planning.</i>

Introduction

The twenty-first century has been characterized by unprecedented urban growth accompanied by substantial advances in digital technology. The United Nations projects that approximately 70% of the global population will reside in urban areas by 2050, thereby intensifying the importance of effective urban governance, sustainable infrastructure, and intelligent spatial planning (United Nations 2018). As contemporary cities become increasingly complex and interconnected, conventional planning approaches that depend predominantly on demographic statistics, generalized population projections, and periodic surveys are increasingly inadequate for capturing the rapidly changing conditions of urban life. Within this context, the concept of the smart city has gained considerable prominence. Smart city strategies emphasize the integration of advanced technologies, continuously updated data, and intelligent analytical systems to improve environmental sustainability, urban livability, service efficiency, and the overall capacity of cities to respond to changing conditions.

One of the fundamental challenges in smart city development concerns the accurate understanding of how people actually occupy, experience, and use urban spaces. For decades, urban planners and designers have relied on predetermined regulations, formal spatial classifications, and planned functional structures to organize urban environments. Nevertheless, empirical evidence increasingly demonstrates that actual human behavior does not necessarily correspond to officially intended spatial functions. Parks, streets, commercial districts, waterfronts, and public gathering areas may acquire uses that differ substantially from their original planning objectives. This condition requires alternative approaches capable of documenting everyday behavior and translating behavioral information into meaningful spatial knowledge. Consequently, there is a growing need for methodologies that can continuously capture how people actually use and move through urban environments (Yang and Zhen 2024; Liaros 2019; Atmaheni and Adianto 2024).

Historically, the investigation of human use of space within buildings and urban environments has depended substantially on direct observation, interviews, questionnaires, and other conventional behavioral research techniques.

Developments in environmental-behavior research have demonstrated that human actions and spatial environments maintain a reciprocal relationship in which behavior is influenced by spatial conditions while spatial environments are simultaneously modified through human activities. Similarly, urban researchers have demonstrated that the success and vitality of public spaces are determined to a significant extent by how those spaces are actually occupied and used rather than by their visual qualities or formal design characteristics alone (Almulhim 2025).

These early methodological approaches have contributed substantially to the development of behavioral architecture and behavioral design. However, they also present important limitations. Manual observation of users, for example, is highly labor intensive, generally restricted to particular observation periods and geographic areas, and potentially vulnerable to subjective interpretation and observer bias (Indira Dewi et al. 2021). Conventional behavioral mapping techniques likewise tend to provide relatively short-term representations of activities rather than continuous records of movement and interaction over extended periods. Although these approaches have established important theoretical foundations for understanding the relationship between people and space, they leave considerable opportunities for developing more accurate, continuous, and scalable methods of behavioral-spatial investigation.

The emergence of smartphones, Global Positioning System (GPS) technologies, cloud computing, and location-based services has substantially transformed the manner in which urban behavior can be investigated. On a daily basis, people generate digital traces through navigation applications, social media platforms, mobile services, and other location-sensitive technologies. These digital traces provide extensive opportunities to examine movement patterns, frequently visited locations, activity concentrations, and the temporal dimensions of spatial use. Accordingly, data generated through everyday digital activities have created new possibilities for understanding urban environments at a level of continuity and scale that would be difficult to achieve through conventional observation techniques alone (Sia, Saidin, and Iskandar 2023; Doyle-Baker et al. 2021).

Recent developments in Geographic Information Systems (GIS), urban analytics, and spatial computing have further enabled researchers to employ location-based data to investigate urban mobility, transportation behavior, destination choices, place visitation, and interactions between people and their surrounding environments. Among the various digital platforms available for spatial analysis, Google Maps and its associated API services are particularly significant because of their extensive geographic coverage, frequent data updates, and capacity to integrate multiple categories of spatial information (Budnicka-Kosior et al. 2025; Hasibuan et al. 2014). Services such as the Places API, Directions API, Distance Matrix API, and Traffic Layer provide opportunities to represent, contextualize, and analyze patterns of human activity across different urban settings. This technological transformation reflects a broader conceptual shift in urban studies: the emphasis is moving from static representations of physical space toward dynamic, data-driven interpretations of how urban environments are continuously occupied, traversed, and transformed.

Several theoretical perspectives support this methodological and conceptual transformation. Behavioral Architecture emphasizes the reciprocal relationship between spatial environments and human behavior. From this perspective, physical environments influence how people act, move, interact, and occupy space, while repeated human activities can simultaneously modify and redefine the meaning and function of those environments.

Environmental Psychology similarly investigates the ways people perceive, interpret, experience, and behave within built environments. Together, these perspectives provide an important theoretical foundation for examining spatial use as a central dimension of architectural and urban inquiry (Kirsh 2025; Kim, Park, and Choo 2021).

Space Syntax, developed by Bill Hillier and his colleagues (Yamu, van Nes, and Garau 2021), represents another influential theoretical framework for analyzing spatial relationships. It provides systematic methods for examining spatial configuration and for interpreting potential movement according to spatial connectivity, integration, accessibility, and other configurational properties. Space Syntax has become highly influential within urban morphology and spatial analysis because it

provides a means of relating spatial configuration to patterns of movement. Nevertheless, many applications primarily emphasize the configuration of space and frequently rely on predicted or modeled movement rather than continuously observed behavioral evidence. The integration of actual behavioral data with configurational analysis could therefore provide a more comprehensive understanding of how spatial structures operate in real urban environments (Yamu, van Nes, and Garau 2021).

Spatial Behavior Theory provides another useful perspective for explaining how individual actions contribute to broader urban configurations. Repeated movements, everyday activities, destination choices, and habitual routes collectively generate routines that influence the organization and use of urban space. From this perspective, cities are not produced exclusively through large-scale interventions or formal planning decisions made by governmental institutions. Rather, urban structures also emerge through the accumulated effects of everyday activities and repeated behavioral practices. Urban form can therefore be understood as an evolving outcome of continuous interactions between human behavior and spatial environments (Yamu, van Nes, and Garau 2021; Vaughan, Peponis, and Dalton 2025).

Digital Urbanism provides an additional conceptual lens through which contemporary urban transformation can be interpreted. It considers cities as interconnected systems in which physical and digital environments are becoming increasingly intertwined. Within this framework, digital data function as behavioral traces or indicators of ongoing urban processes, providing information about activities, movements, interactions, and transformations occurring within the city. Instead of conceptualizing the city as a fixed geographical entity, Digital Urbanism emphasizes the city as a dynamic network shaped by information flows, technological development, digital infrastructures, and the people who continuously interact with these systems (El-Bardisy 2024).

The theoretical framework of Complex Adaptive Systems is similarly relevant to the analysis of contemporary urban environments. Modern cities demonstrate characteristics such as self-organization, emergence, nonlinearity, adaptation, and continuous transformation. Urban spatial configurations develop through numerous interactions among individuals, communities,

institutions, infrastructures, technologies, and environmental conditions. Consequently, observed urban patterns should not necessarily be interpreted exclusively as the direct consequences of top-down planning. Many spatial patterns emerge organically from collective behavior and repeated interactions among urban users. Particular places, movement routes, activity concentrations, and social clusters can therefore develop as emergent outcomes of interactions among multiple urban agents, producing spatial environments that remain dynamic and continually subject to change (Abujder Ochoa et al. 2024).

Despite significant advances in urban analytics and smart city research, several important research gaps remain. A substantial proportion of studies that employ location-based data continue to emphasize transportation optimization, traffic management, or mobility efficiency rather than reconstructing urban spatial structures directly from behavioral evidence. Existing behavioral studies also frequently treat movement data primarily as descriptive information without developing sufficiently robust theoretical relationships between individual behavior and broader spatial configurations. Furthermore, relatively limited research has integrated mobile behavioral tracking systems with real-time digital mapping platforms to develop adaptive representations of urban environments. Consequently, there remains a need for clearer conceptual and methodological frameworks capable of explaining how individual spatiotemporal behaviors collectively contribute to the emergence and transformation of urban spatial structures.

This study addresses these gaps through the development of a Digital Behavior Spatial Model (DBSM). The model integrates Takunai, a mobile-based spatial-temporal tracking application, with Google Maps API to facilitate real-time spatial analysis and visualization. In contrast to conventional approaches that define urban areas according to administrative boundaries, predetermined land-use categories, or formal planning functions, the proposed model interprets urban space through the actual behavior of its users. By recording movement trajectories, activity hotspots, visitation frequencies, and temporal patterns, the model reconstructs aspects of urban spatial organization directly from behavioral evidence.

The study makes three principal contributions. First, it conceptualizes urban space as a dynamic behavioral system rather than merely as a collection of static physical locations. Second, it integrates mobile behavioral tracking and real-time spatial visualization into a unified analytical framework for investigating urban environments. Third, it establishes a relationship between detailed individual behavioral information and broader urban spatial structures through continuous data analysis. Collectively, these contributions support a transition in behavioral urban studies from predominantly descriptive observation toward computationally supported and evidence-driven spatial analysis.

The study has three principal objectives. First, it seeks to identify and analyze the temporal and spatial patterns of human movement within the Kupang waterfront area through digital behavioral tracking. Second, it investigates how individual movement patterns collectively contribute to the formation of activity nodes, movement corridors, and emerging spatial structures. Third, it aims to develop and evaluate a Digital Behavior Spatial Model capable of supporting evidence-based urban planning and design.

The significance of this research extends beyond methodological innovation. The study contributes to contemporary understandings of urban spatial formation by bringing together perspectives from Behavioral Architecture, Environmental Psychology, Space Syntax, Digital Urbanism, and Complex Adaptive Systems within an integrated analytical framework. The findings demonstrate that the combination of behavioral tracking technologies and spatial analytics can provide a basis for continuously monitoring urban conditions. For urban planners and policymakers, the proposed model offers a data-driven approach for observing spatial transformation, evaluating patterns of space use, and developing adaptable urban environments. Ultimately, the study supports a broader transition from static, regulation-oriented urban planning toward more intelligent, behavior-responsive management of contemporary digital cities.

Methods

The present study adopts a quantitative computational methodology within a model-development research design, through which a Digital Behavior Spatial Model (DBSM) is developed as an analytical means of reconstructing urban spatial configurations from patterns of human behavior. Unlike conventional urban research approaches that depend primarily on administrative zoning systems, land-use classifications, and survey-based methodologies, the present approach conceptualizes urban spaces as emergent entities generated through continuous spatiotemporal interactions among individuals and their surrounding urban environments.

The conceptual model underlying this research is founded on the proposition that individual actions generate spatiotemporal footprints that accumulate into recognizable patterns of collective behavior. As these behavioral patterns are repeated over time, they contribute to the formation of activity nodes, movement corridors, and gradients of spatial intensity. Collectively, these components constitute an empirically observable representation of urban spatial structure. The conceptual framework consists of four principal stages: data collection, spatiotemporal analysis, extraction of spatial structures, and formulation of the Digital Behavior Spatial Model. The behavioral data-collection stage involves gathering information on individual movements and activities recorded through GPS-enabled mobile devices. The analytical stage subsequently transforms these behavioral records into density surfaces, movement networks, and matrices representing spatial interactions.

The empirical investigation was conducted within the waterfront development area located along Kupang Bay, Kupang City, East Nusa Tenggara, Indonesia. The selected study area is characterized by a highly dynamic waterfront environment in which formal planning interventions, informal economic activities, tourism and recreational destinations, and transportation routes coexist and interact. Considerable spatial development has occurred throughout the area during the past decade, making the site appropriate for examining discrepancies between planned urban functions and actual patterns of spatial use. Two major components were identified within the study area:

the relatively developed waterfront corridor extending from Handayani Restaurant to Suba Suka Restaurant and the less-developed coastal segment extending from Tedys Bar to Ketapang Satu.

The data-collection process integrated a mobile behavioral-tracking application known as Takunai with Google Maps APIs. Takunai functioned as the principal behavioral data-collection instrument and recorded users' positions at regular temporal intervals. The information collected through Takunai included latitude, longitude, timestamp, duration of presence at particular locations, revisit frequency, and movement trajectories. In parallel, Google Maps APIs supplied geospatial representations and supplementary contextual information through the Traffic Layer, Places API, Directions API, and Distance Matrix API services.

The Takunai-Google Maps system architecture consists of four interconnected modules designed to support the overall analytical process. First, the behavioral-tracking module records behavioral information through GPS coordinates together with temporal information obtained from mobile devices. Second, the cloud-storage module retains the collected behavioral records and supports their synchronization in real time. Third, the geospatial-processing module converts the captured GPS coordinates into structured and analyzable spatial information. Fourth, the visualization and analysis module employ the Google Maps API to represent movement trajectories, heat maps, activity clusters, and spatial interaction networks.

Spatial and temporal data were collected continuously throughout a fourteen-day observation period. Participants used the Takunai application on Android-based mobile phones, allowing their locations to be recorded automatically during observation. The resulting dataset included geographic coordinates, timestamps, movement durations, and sequential trajectory information. Observations were conducted across different periods of the day, including morning, afternoon, evening, and nighttime, thereby enabling the identification of behavioral differences associated with different temporal conditions.

Prior to analytical processing, the collected datasets underwent a preprocessing procedure designed to improve data quality, consistency, and reliability. Raw GPS records may contain positional inaccuracies resulting from signal

interference, device-specific limitations, and environmental conditions. To address these potential sources of error, spatial filtering was applied and anomalous records were removed as outliers. Duplicate and incomplete observations were also excluded. Temporal synchronization was subsequently conducted to maintain consistency among records obtained from different data sources. In addition, all spatial coordinates were standardized according to the WGS 84 coordinate reference system.

Following preprocessing, activity nodes were extracted to identify locations characterized by relatively high concentrations of human activity. An activity node was defined as a geographic location exhibiting a high frequency of activity combined with relatively long durations of stay. Density-based clustering analysis was employed to identify these locations. Places demonstrating repeated patterns of behavioral concentration were classified as candidate activity nodes. The strength of each identified node was subsequently calculated from the aggregate intensity of activities occurring at that location.

To quantify the intensity of activity, the following formulation was employed:

$$AI_i = \sum_{j=1}^n (D_{ij} \times V_{ij})$$

where:

AI_i = activity intensity at location i ,
 D_{ij} = duration of activity j at location i ,
 V_{ij} = visitation frequency of activity j ,
 n = number of observations.

The analysis subsequently examined movement corridors to determine the principal routes connecting different activity nodes. Movement corridors were conceptualized as routes generated by repeated movements of users between two or more locations. Each identified corridor was represented as an edge within a spatial network connecting an origin node and a destination node.

Movement frequency was calculated using:

$$MF_{ij} = \frac{T_{ij}}{\sum T}$$

where:

MF_{ij} = movement frequency between nodes i and j ,
 T_{ij} = number of observed trips between nodes,
 $\sum T$ = total observed trips within the study area.

Density-mapping techniques were subsequently employed to visualize the spatial distribution of observed activities. Kernel Density Estimation (KDE) was applied to generate density surfaces from behavioral observations. This procedure enabled the identification of locations in which activities occurred with relatively high frequency, thereby revealing gradients of spatial intensity across the waterfront environment.

Spatial density was calculated as:

$$SD(x) = \sum_{i=1}^n K\left(\frac{x - x_i}{h}\right)$$

where:

$SD(x)$ = spatial density at location x ,
 K = kernel function,
 x_i = observed activity point,
 h = bandwidth parameter.

Spatial-interaction analysis was undertaken to assess the level of interaction among identified activity nodes. Using a gravity-based spatial-interaction modeling approach, the degree of interaction was estimated according to visitation intensity and spatial distance between locations.

The interaction model was formulated as:

$$SI_{ij} = \frac{P_i \times P_j}{d_{ij}^\beta}$$

where:

SI_{ij} = spatial interaction between nodes i and j ,
 P_i and P_j = activity intensities,
 d_{ij} = distance between nodes,
 β = distance decay coefficient.

Spatial-network analysis was conducted to investigate the structural properties of the behavioral network generated by urban activities and movements. Within this network representation, activity nodes were modeled as vertices, while movement connections were represented as edges. Measures derived from graph theory were employed to evaluate network connectivity, hierarchy, and centrality, with particular attention given to identifying dominant

nodes that function as anchors for activity within the waterfront environment.

Network centrality was measured using degree centrality:

$$C_D(i) = \frac{k_i}{N - 1}$$

where:

$C_D(i)$ = degree centrality of node i ,

k_i = number of connected edges,

N = total number of nodes.

Model validation was conducted through an iterative procedure involving field verification, comparison with existing land-use plans, and sensitivity testing. Observed behavioral nodes and movement paths were examined against the empirical data collected during fieldwork. The resulting behavioral structures were then compared with established land-use plans to identify areas of correspondence and divergence between planned functions and observed patterns of spatial use. A further stage of validation involved sensitivity analysis through systematic adjustments to clustering parameters and density factors.

Ethical considerations constituted an integral component of the research methodology.

Participation in behavioral monitoring was voluntary, and informed consent was obtained from all participants before any behavioral data were collected. Personal identifying information was removed from the dataset during preprocessing to protect participant privacy. Geographic-location data were subsequently analyzed at an aggregated level, thereby reducing the possibility of associating specific spatial records with individual users.

Results and discussion

The integration of Takunai with the Google Maps API produced a spatiotemporal dataset representing the actual movement patterns of users within the Kupang Bay waterfront area. During fourteen days of behavioral monitoring and mobile-based trajectory recording, the collected dataset contained latitude-longitude coordinates, timestamps, durations of stay, visitation frequencies, and movement trajectories. Following the data-cleaning process, a total of 4,836 valid spatial records remained available for analysis.

Table 1. Dataset characteristics

Variable	Description	Value
Observation period	Continuous monitoring	14 days
Participants	Active tracked users	5
GPS records collected	Raw observations	5,214
Valid observations	After preprocessing	4,836
Activity nodes identified	High-density clusters	12
Major movement corridors	Dominant trajectories	8
Average daily observations	Records/day	345
Average stay duration	Minutes	28.4
Maximum stay duration	Minutes	126.0
Average movement distance	Kilometers	3.8

Descriptive analysis indicates substantial variation in the movement behavior of individual users. The mean dwell time of approximately 28 minutes suggests that the waterfront functions not merely as a transportation corridor but also as a destination for recreational, social, and economic activities. The substantial number of valid observations further demonstrates that the integrated Takunai-Google Maps approach was capable of capturing spatiotemporal movement patterns continuously across an extended observation period. This finding is particularly relevant to behavioral-based urban analysis

because the resulting dataset provides a more continuous representation of spatial use than would ordinarily be possible through isolated periods of manual observation.

User movement characteristics

Analysis of the movement trajectories recorded for each participant demonstrates considerable behavioral heterogeneity. Some participants exhibited relatively concentrated trajectory patterns associated with routine activities and recurring destinations, whereas others demonstrated more exploratory movement

patterns involving multiple transitions among different locations. Despite these individual differences, a common tendency was observed: a substantial proportion of participant movements occurred along the coastal corridor extending between Pasir Panjang and Kelapa Lima.

The trajectory analysis further indicates that participants tended to select routes providing access to recreational destinations, food and culinary facilities, waterfront amenities, and transportation services. This behavioral pattern suggests that both accessibility and the diversity of available activities influence the selection of movement trajectories within the study area. Locations offering multiple opportunities for different activities appear to function as important attractors within the broader movement network.

Another significant behavioral pattern is the concentration of movement around locations characterized by functional diversity. Rather than moving randomly across the urban environment, users tended to visit specific destinations where several complementary activities could be undertaken. This observation suggests that spatial attractiveness is associated not simply with a single land-use function but with the coexistence and accessibility of multiple activities. Such a pattern is consistent with previous findings indicating that urban vitality can be influenced substantially by the intensity, diversity, and interaction of activities occurring within a given spatial environment.

Spatial-Temporal distribution patterns

The analysis of spatiotemporal distribution reveals noticeable differences in activity intensity across different periods of the day. During the early morning period, between 06:00 and 10:00, activities were concentrated primarily along transportation corridors and commercial areas. During the midday period, from approximately 10:00 to 15:00, activity intensity increased around shopping centers and service-oriented destinations.

These findings indicate that the spatial structure of the waterfront is not constant

throughout the day. Instead, its organization changes according to temporal cycles associated with different patterns of human activity. Urban space should therefore be interpreted as an evolving process rather than exclusively as a static physical configuration. The same physical environment may accommodate different groups, activities, movement patterns, and social functions at different times.

Three chronological stages were observed:

- Functional Stage (Morning) – characterized primarily by work-related activities, commercial transactions, and routine movement.
- Transitional Stage (Afternoon) – characterized by the coexistence and interaction of economic and social activities.
- Recreational Stage (Evening) – characterized predominantly by recreation, leisure, social interaction, and waterfront-oriented activities.

The transition from predominantly functional spaces during the daytime to increasingly recreational spaces during the evening provides an example of temporal spatial reorganization. In this process, the same physical environment assumes different roles according to the time of day and the behavioral patterns of its users. This finding reinforces the importance of incorporating temporal dimensions into urban spatial analysis rather than interpreting spatial function solely through fixed land-use classifications.

Activity node identification

Density-based clustering analysis identified twelve significant activity nodes distributed throughout the waterfront area. These nodes represent locations at which users repeatedly converged, resulting in relatively concentrated patterns of behavioral activity. Their identification provides an empirical representation of activity concentration that may differ from formal planning classifications.

Table 2. Activity node ranking

Rank	Activity Node	Activity intensity score
1	Aston Waterfront Area	0.921
2	Kelapa Lima Beach	0.885
3	Lippo Plaza Area	0.817
4	Culinary Corridor	0.796
5	Public Waterfront Park	0.751
6	Traditional Fish Market	0.702

Rank	Activity Node	Activity intensity score
7	Coastal Sports Area	0.668
8	Transportation Hub	0.621
9	Community Gathering Space	0.593
10	Hotel Commercial Zone	0.556
11	Local Retail Cluster	0.532
12	Residential Access Node	0.487

The ranking demonstrates a clear differentiation in activity intensity among the identified nodes. The Aston Waterfront Area records the highest activity intensity score, followed by Kelapa Lima Beach and the Lippo Plaza Area. These results indicate that locations associated with recreational, commercial, and mixed activities occupy prominent positions within the behavioral structure of the waterfront. Lower-ranked nodes remain relevant because their activity patterns contribute to the connectivity and functional diversity of the broader spatial system.

Movement corridor analysis

Movement-corridor analysis identified eight principal pathways connecting the activity nodes. These corridors represent recurring movement trajectories through which users repeatedly travel between destinations. Their identification provides insight into the behavioral organization of the waterfront beyond the spatial distribution of individual activity nodes.

Table 3. Movement Intensity Matrix

Origin-Destination	Intensity
Aston – Kelapa Lima	0.89
Aston – Lippo Plaza	0.82
Kelapa Lima – Culinary Corridor	0.79
Lippo Plaza – Commercial Zone	0.76
Aston – Fish Market	0.73
Waterfront Park – Sports Area	0.68
Commercial Zone – Residential Node	0.61
Transportation Hub – Waterfront	0.58

The strongest movement corridor was the connection between the Aston Waterfront Area

and Kelapa Lima Beach, which recorded an intensity value of 0.89. This corridor functions as a principal recreational artery within the waterfront system and reflects a recurring pattern of movement among users. Its prominence indicates that the spatial relationship between major recreational destinations is an important component of the behavioral organization of the area.

The overall network of movement corridors further demonstrates that mobility is strongly influenced by complementary activities. Users frequently moved between locations that perform different but mutually supportive functions, including recreation, dining, shopping, and transportation. Such movement behavior indicates that destinations are not isolated spatial units; instead, they form interconnected activity networks in which the attractiveness of one location can be reinforced by its relationship with other destinations. The findings therefore support the relevance of activity-network concepts in understanding the organization of urban environments.

Heatmap and density analysis

Kernel Density Estimation generated heat maps representing the distribution of behavioral intensity across the study area. The resulting density surfaces reveal distinct spatial differentiation among areas characterized by very high, high, medium, low, and very low activity intensity. This differentiation makes it possible to interpret the waterfront not as a uniformly used environment but as a spatial field containing varying levels of behavioral concentration.

Table 4. Density classification

Density level	Density value	Spatial interpretation
Very High	>0.80	Primary activity core
High	0.60–0.80	Secondary activity node
Medium	0.40–0.60	Mixed-use transition zone
Low	0.20–0.40	Peripheral activity area
Very Low	<0.20	Sparse activity zone

Three principal clusters were identified along the waterfront route based on the heat map generated from the behavioral data and contextual

information obtained through the Google Places API. These clusters indicate areas in which

repeated human activity produced comparatively high levels of spatial intensity.

An important observation is that several dense behavioral clusters were detected in locations that do not correspond directly to officially designated urban areas. This discrepancy is analytically significant because it suggests that actual patterns of urban use can extend beyond the boundaries

and functional categories established through formal planning. The behavioral map therefore provides an empirical perspective on how users appropriate, connect, and activate urban environments in ways that may not be anticipated by conventional spatial classifications. Figure 1 illustrates the resulting behavioral spatial pattern.

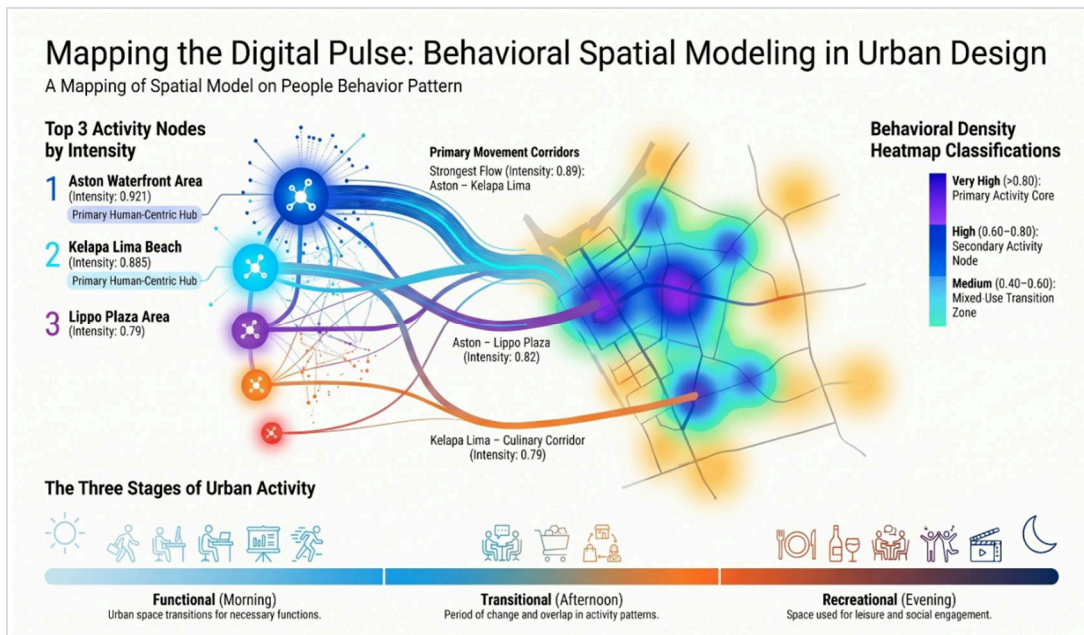


Figure 1. Mapping Spatial Model people behavior

Theoretical implications

The findings generate several implications for established theories of urban space and behavior.

- In relation to Batty's Complex Cities theory, the emergence of activity nodes and movement corridors illustrates the principle of self-organization within urban systems. Spatial concentrations do not necessarily develop exclusively through top-down planning interventions. Instead, they can emerge through the continuous interactions among individuals who use, traverse, and adapt urban spaces in their everyday activities. The identified nodes and corridors therefore provide empirical evidence that collective behavior can contribute to the spontaneous organization of urban spatial structures.
- From the perspective of Castells' concept of the Space of Flows, the findings demonstrate that the significance of urban locations is increasingly related to movement, connectivity, and relational accessibility

rather than geographic position alone. Activity nodes become important not simply because of where they are physically located but also because of how effectively they are integrated into behavioral networks. A location with strong connections to multiple destinations can therefore acquire greater functional significance through its position within the network of urban flows.

- The findings are also consistent with Lefebvre's theory of the Production of Space. The observed discrepancy between formal planning classifications and actual patterns of spatial use indicates that urban space is continually produced and reproduced through everyday social practices. The behavior of users, their movements, activities, interactions, and repeated appropriation of places contribute to the ongoing production of spatial meaning and function. Consequently, urban space cannot be understood solely as a physical product of planning and design; it

must also be interpreted as a social and behavioral process.

- d. With regard to the Space Syntax theory developed by Hillier, the findings suggest that spatial configuration plays an important role in influencing movement but cannot be regarded as the sole determinant of behavioral patterns. Other factors, including activity potential, economic functions, destination attractiveness, and social interaction, also contribute to movement decisions. Behavioral evidence therefore provides an important empirical dimension that can complement configurational analysis. Integrating observed behavioral data with spatial-configuration analysis may produce a more comprehensive explanation of movement patterns within complex urban environments.

Finally, Gehl's theory of Public Space Behavior provides another relevant perspective for interpreting the findings. Areas characterized by high activity intensity correspond substantially with environments that support social interaction, pedestrian circulation, recreation, and mixed-use activities. This correspondence reinforces the importance of designing and managing public spaces in ways that accommodate actual patterns of social and behavioral use rather than relying exclusively on predetermined functional assumptions.

Conclusions

The Digital Behavior Spatial Model (DBSM) developed in this study combines Takunai, a smartphone-based spatial-temporal behavioral tracking application, with Google Maps APIs to investigate real-time patterns of spatial behavior within the Kupang waterfront area. The central question addressed by the research is whether urban spatial structures can be reconstructed from actual human behavior rather than being defined exclusively through formal zoning systems and conventional urban planning techniques. The findings demonstrate that digitally collected behavioral data can provide a powerful empirical foundation for identifying and interpreting patterns of urban spatial organization, many of which may remain underrepresented or overlooked within conventional urban planning approaches.

The empirical results indicate that human movement throughout the study area is organized around activity nodes, principal movement corridors, and spatial gradients of behavioral intensity. Analysis of GPS trajectories, visitation frequencies, and durations of stay revealed numerous activity centers distributed along the coastal corridor. Rather than producing a purely monocentric spatial configuration dominated by a single activity node, the study area demonstrates a semi-polycentric structure composed of multiple recreational, commercial, and mixed-use nodes. The locations exhibiting the greatest activity intensity include the Aston Waterfront Area, Kelapa Lima Beach, and nearby commercial destinations. Movement-corridor analysis further confirms the existence of recurring pathways connecting these locations. In addition, spatiotemporal analysis identified significant differences in activity patterns between daytime and evening periods, demonstrating that the same physical areas may perform substantially different functions according to temporal conditions.

From a conceptual perspective, the study contributes to contemporary research on urban spatial theory by proposing that space should be interpreted as a dynamic system continuously produced through human behavior. Traditional urban spatial theories have frequently conceptualized space as a relatively stable phenomenon organized through formal zoning systems, planning regulations, and institutional mechanisms. The Digital Behavior Spatial Model, in contrast, conceptualizes urban space as a continuously changing configuration emerging from the cumulative behavior of individuals and groups. The findings are consistent with several theoretical perspectives, including Behavioral Architecture, Environmental Psychology, Space Syntax, Digital Urbanism, and Complex Adaptive Systems. Through the integration of these perspectives, the study contributes to the growing body of research that interprets urban environments as complex adaptive systems rather than as static physical arrangements.

Methodologically, the research introduces a behavioral-data-driven framework for investigating urban spatial conditions. The combination of mobile behavioral tracking and real-time geographic analysis through GPS provides a scalable and potentially replicable approach to examining urban dynamics. In contrast to conventional behavioral-mapping

approaches that depend heavily on direct observation, the proposed framework enables the continuous recording and analysis of individual movement trajectories. Furthermore, the model supports multiple forms of spatiotemporal analysis, including density mapping, movement-corridor identification, spatial-interaction assessment, activity-node extraction, and network analysis. These capabilities expand the methodological scope of behavioral urban research by enabling individual observations to be transformed into broader representations of urban spatial organization.

From a practical perspective, the proposed approach creates substantial opportunities for urban planners, architects, designers, and policymakers. By providing empirical information regarding where people move, where they remain, and how different destinations are connected, the DBSM can assist planners and designers in developing urban environments that respond more closely to actual patterns of spatial use. In particular, the identification of activity nodes and movement corridors can support more effective decisions concerning infrastructure allocation, public-space planning, transportation systems, pedestrian circulation, and mixed-use development. At a broader scale, the model can support the design of human-centered public environments that are informed by observed behavioral patterns rather than solely by predetermined planning assumptions.

From a policy perspective, digital behavioral tracking creates opportunities for more dynamic and responsive urban planning policies by making urban performance continuously observable. The proposed model could contribute to the development of urban dashboards and decision-support systems capable of monitoring changes in urban environments through the ongoing analysis of movement patterns, activity concentrations, and spatial transformations. Such an approach is particularly relevant to rapidly developing cities, where conventional planning methods may struggle to respond quickly enough to continuously changing patterns of urban activity. Continuous behavioral information can provide policymakers with a more current evidence base for evaluating spatial performance and responding to emerging urban conditions.

Despite its contributions, the study has several limitations that should be addressed in future research. First, the number of participants included in the analysis is relatively small, which

may limit the representativeness and generalizability of the findings. Second, digital behavioral tracking primarily captures movement-related information and therefore cannot fully explain the motivations, perceptions, intentions, or meanings underlying observed behaviors. Third, the analysis was conducted within a geographically limited study area, meaning that the findings cannot be generalized directly to other urban contexts without additional comparative evidence. Fourth, the quality and completeness of digitally collected spatial data depend on several factors, including users' willingness to participate, the availability and performance of mobile devices, GPS signal quality, and the reliability of Internet connectivity.

Future research could address these limitations by substantially expanding the sample size and extending the duration of behavioral observation. The integration of machine-learning and artificial-intelligence techniques could further enhance the predictive and pattern-recognition capabilities of the model. Behavioral datasets could also be complemented with qualitative information obtained through interviews, participant-based research, and ethnographic observation. Such integration would allow researchers not only to identify where and when behaviors occur but also to investigate why particular behavioral patterns emerge. Future investigations could additionally compare behavioral patterns across different waterfronts, cities, cultural contexts, and urban morphologies, thereby contributing to the development of a more comprehensive theoretical framework for understanding the reciprocal relationship between spatial structure and human behavior.

Overall, the findings demonstrate that digital behavior spatial modeling offers a valuable contribution to contemporary research on the structure, dynamics, and transformation of urban space. By aggregating individual behavioral traces into recognizable patterns of urban organization, the DBSM creates new opportunities for understanding how collective human activity contributes to the formation and reconfiguration of urban environments. The proposed approach therefore extends the potential applications of behavioral spatial research across several interconnected fields, including Smart City development, Digital Urban Governance, Real-Time Urban Monitoring, Behavioral-Based Urban Design, and Adaptive Spatial Planning.

More broadly, the study supports a shift toward urban planning and design approaches that recognize behavior as an essential source of spatial knowledge and treat the city as a dynamic, adaptive, and continuously evolving environment.

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Author(s) contribution

Donatus Ara Kian contributed to the research concepts preparation, methodologies, investigations, data analysis, visualization, articles drafting and revisions.

Ridwan Sanjaya contribute to the research concepts preparation and literature reviews, data analysis, of article drafts preparation and validation.

V. G. Sri Rejeki contribute to methodology, supervision, and validation.