# Monitoring tourist digital footprint and tourist activities centers through geotagged and geolocated data: Alexandria city as a case study

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## Abstract

The progression of technology has facilitated the examination of each user interaction and click on electronic devices. Tourists leave a digital "footprint" in most of their activities in the cities they visit; a significant amount of these data is geolocated. Studying the spatial and temporal preferences of individuals and patterns of movement represents a major factor that must be taken into account when designing urban land use policies, as contributions to the study of the spatial behavior of urban tourists in cities are still lacking. Therefore, the present study offers insights into user behavior in urban environments, facilitating the identification and examination of areas where there is a high concentration of tourist activities and enabling the identification of inactive zones within the urban area. The main aim of this research is to introduce a method for monitoring the level of tourist activity pulse in cities by examining User-Generated Content data. The novelty of this study is apparent in several key aspects: firstly, it concentrates on the intersections of eating, shopping, sightseeing, and nightlife activities in a chosen city for the case study; secondly, it presents a novel method for describing urban tourist activity centers and identifying areas of interest from the perspective of users, utilizing Location-Based Social Networking data by employing spatial clustering analysis. Thirdly, the proposed reference framework incorporates LBSN data, serving as a supplementary tool for urban planning and decision-making processes aimed at improving city urban dynamics. In this sense, an exploratory study was carried out using a case-study approach in Alexandria, Egypt by employing a GIS program-QGIS, Prizren 3.32 version. The findings of this study have significant implications for tourism destination managers, urban planners and scientists interested in the analysis of urban dynamics, to orientating urban land-use planning and formulating tourism strategies that align with urban revitalization and regeneration to address imbalances in various areas.

**Key words:** tourist digital footprint, tourist activities centers, Location-Based Social Networks, geotagged and geolocated data, spatial analysis, urban planning, Alexandria.

## Introduction

In recent years, Big Data have shown significant potential in the field of tourism research, owing to their ability to offer spatiotemporal data derived from a large number of tourists (Salas Olmedo et al., 2018). The progression of technology has facilitated the capture and examination of each user interaction and click on electronic devices, forming a digital foot print (Bondarenko et al., 2021), which plays a crucial role in comprehending the spatiotemporal trends in tourist decision-making processes, thus enabling the identification of tourist preferences and formulation of tourism strategies (Cebrián & Domenech, 2023).

Notably, the emergence of social media has had a significant impact on the field of tourism, being extensively utilized in various research studies. These studies range from the segmentation of tourist markets using user-generated content (UGC) to exploring the behaviors within online tourist communities. Scholars such as Li et al. (2018), Yubero et al. (2021), and Nolasco-Cirugeda et al. (2022) have delved into this phenomenon. Social media platforms have effectively engaged tourists, offering them a space to exchange insights and information concerning their travel experiences as well as finding sophisticated method to illustrate individuals' spatiotemporal preferences and mobility patterns (Yu et al., 2023).

Indeed, Data obtained from Location-Based Social Networks (LBSNs) and other forms of social media data are valuable for examining socio-spatial behavior patterns within urban cities. These data facilitate the visualization of segmented variables and the identification of Points of Interest (POIs) or Areas of Interest (AOIs) within urban centers (García-Palomares et al. 2015; Li et al. 2018). Furthermore, the analysis of LBSN data, supported by dynamic georeferenced User-Generated Content (UGC) and metadata, proves beneficial for investigating disparities and imbalances such as those arising from over tourism (Nolasco-Cirugeda et al., 2022; Encalada-Abarca, et al., 2024) or the uneven distribution of tourist flows towards specific tourist areas, leading to issues like visitor overcrowding in specific tourist zones (Jiansheng &Yanling, 2021). This phenomenon elucidates the issue of overcrowding or clustering of visitors, including tourists and local inhabitants (Jiansheng & Yanling, 2021), in areas with particular tourist attractions while neglecting other dispersed urban tourist spots offering diverse activities and amenities. According to the aforementioned, studying the spatial and temporal preferences of individuals and patterns of movement represents a major factor that must be taken into account when designing urban land use policies, as contributions to the study of the spatial behavior of urban tourists in cities (Salas-Olmedo et al. 2018) are still lacking.

Therefore, the present study offers insights into user behavior in urban environments, facilitating the identification and examination of areas where there is a high concentration of tourist activities (Kim et al., 2021). Additionally, it enables the identification of inactive zones within the urban area. This has the potential to furnish urban planners and stakeholders with up-to-date data (Martí et al., 2021) to enhance and implement strategies that enhance connectivity and quality of life in less attractive areas.

Employing an exploratory approach, the main objective of this research is to introduce a method for monitoring the level of tourist activity pulse in cities by examining User-Generated Content (UGC) data. This encompasses three supplementary objectives:

(1) The identification of Tourist Activity Center areas – TAC areas – utilizing the Instasights Heatmaps tool to pinpointing key areas with high levels of tourism-related activities such as sightseeing, eating, shopping and nightlife.

(2) The determination of current portrayal of urban activities and prominent tourist-centric locations within the identified TAC areas using data from four Location-Based Social Networks (LBSNs) – Instasights, Foursquare, Twitter, Instagram, and TripAdvisor.

(3) The examination of the digital footprint application in studying tourism flow patterns offering a theoretical reference for developing tourist itineraries and promoting collaboration among different tourist attractions.

According to the defined objective, the study focuses on following research questions: 1) How can the pulse of tourism activity in cities be determined based on the analysis of user-generated content data in order to identify tourist activity center areas? 2) What is the possibility of using spatial analysis tools to analyze the distribution and concentration of tourism activities at the level of the study area? 3) How can the possibility of analyzing the mechanisms of tourist flow within cities be determined through the application of digital foot print? 4) What is the proposed framework for describing and characterizing urban tourism activity centers and identifying the main areas of attraction from the user's perspective, through LBSN data?

The novelty of this study is apparent in several key aspects: firstly, it concentrates on the intersections of eating, shopping, sightseeing, and nightlife activities in a chosen city for the case study (Martí et al., 2021); secondly, it presents a novel method for describing and characterizing urban tourist activity centers and identifying Areas of Interest (AOIs) from the perspective of users, utilizing Location-Based Social Networking (LBSN) data (Encalada-Abarca, et al., 2024). Consequently, it becomes possible to recognize the venues preferred by tourists, enabling the verification of urban areas that attract tourists' attention and providing guidance for the city's development based on patterns of user activity (Nolasco-Cirugeda et al., 2022). Thirdly, the proposed reference framework incorporates LBSN data, serving as a supplementary tool for urban planning and decision-making processes aimed at improving city urban dynamics (Gao et al., 2024) and to achieve organized tourism development of cities supporting the wellbeing of current and future tourists flow (Sedarati, 2019).

In this sense, an exploratory study was carried out using a case-study approach in Alexandria, Egypt. The applied methodology allowed validation of the method's suitability to reveal dynamics of urban tourism and offer valuable insights.

Thus, the research makes significant contributions to tourism destination managers, to formulate evidence-based policies for urban tourism development (Yu et al., 2023). Moreover, this work offers a scientific foundation for enhancing and managing tourism spaces, traffic, and service facilities in specific regions (Gu et al., 2023). This approach can also contribute to orientating urban land-use planning (Mou, 2022) and formulating tourism strategies that align with urban revitalization and regeneration (Yubero et al., 2021) to address imbalances in various areas, thus mitigating issues like over-tourism (Nolasco-Cirugeda et al., 2022), gentrification, and uneven distribution of tourist flow towards specific destinations.

## Literature Review

### Big Data, Tourist Digital footprint and Location Based Social Networks (LBSNs): comprehensive overview

The term **'Big Data'** refers to the generation of substantial amounts of machine-readable data. (Üsküplü, Terzi,& Kartal, 2020). This data originates from systems with which users frequently interact in their daily routines. These systems include social media platforms, mobile phone networks, online search engines, various sensors, wearable technology, GPS tracking, water and electricity usage records, weather information, video recordings, and credit card transactions (Reif & Schmücker, 2020; Yubero et al., 2021). Analyzing these datasets enables us to gain a deeper insight into our interactions within urban environments (Waiyausuri et al., 2023; Gao et al., 2024). Big data is distinct from traditional data on several levels. It is extensive (measured in terabytes or mostly petabytes of data), dynamic (created in real-time), varied (stretched from a wide range of sources, including texts, images, videos, tables, and HTM files) (Raun et al., 2016), detailed and comprehensive (usually containing a much larger sample size than traditional datasets), interconnected, and economical (derived from nature) (Kitchin 2014; Üsküplü, Terzi, & Kartal, 2020 ).

In this context, Big Data holds great potential for tourism research as it provides spatiotemporal information generated from numerous tourists (Salas-Olmedo et al., 2018; Martí Ciriquián et al., 2021; Yubro et al., 2021). Meanwhile, Vu, Li &Law (2015) pointed out that researchers examine the behavior of inbound tourists by using geotagged photos. Furthermore, social media has emerged as a major source of highly accurate and instantly updated geographic data (Gao, 2024) that is referred to as **"digital footprints"** (Girardin et al. 2008). In fact, tourists leave a digital "footprint" in most of their activities in the cities they visit (Wu, 2022).They use bank cards to make payments, snap vast numbers of photographs and post them to photo-sharing websites, communicate on social media and mobile devices (Cebrián & Domenech, 2023). According to Jianheng and Yanling (2021), a significant amount of these data is geolocated, so these electronic traces may reflect the temporal and geographical movement trajectory of tourists. This enables researchers to identify the spatial structure and evolution law of the tourism flow (Gu et al., 2023). Multiple studies have explored the spatial network structures of tourist flows using online footprints (Jiansheng & Yanling, 2021; Mou, 2022; Yu, 2023). Aspects of tourist flow and tourist digital footprints are interconnected and are studied through network analysis methods in tourism research (Bondarenko et al., 2021). Consequently, Social media data is employed to evaluate tourist flow to understand travel patterns and location attractiveness, incorporating comments and likes as indicators of tourism intensity and interest (Paldino et al., 2015; Weismayer et al., 2023).

Accordingly, tourism activity centers including shopping, eating, and nightlife are recognized by tourists' digital footprints (Mor & Dalyot, 2020; Yu et al., 2023). In this regard, identifying tourist hotspots or area of interest is critical from the perspectives of urban planning and tourism management in order to ensure accurate design of land-use and tourism-related urban policies (Martí Ciriquián et al., 2019; Nolasco-Cirugeda et al., 2022).

In this field, **location Based Social Networks** ( LBSNs) have been extensively utilized as crucial big data sources for urban analysis (Martí et al., 2021), to providing a method for evaluating the activity pulse of the city (Martí Ciriquián et al., 2019), human mobility (Li et al., 2018), human behavior (Lee et al., 2013), urban planning, urban design, and decision-making processes (Padrón-Ávila & Hernández-Martín, 2017; Üsküplü et al., 2020).

In fact, a comprehensive literature review on the application of big data to tourism has been provided by Li et al. (2018) and by Salas-Olmedo et al. (2018). More specifically, previous researches on points of interest (POIs) sourced by LBSNs have mainly focused on travel behavior and tourist trajectories in order to provide customized suggestions using TripAdvisor (Van der Zed & Bertocchi, 2018) or Foursquare (Dietz et al. 2020; Stamatelatos et al. 2021) in conjunction with additional geolocated data (Nolasco-Cirugeda et al., 2022) from social networks, including Twitter or Yelp.

Social media data integration with GIS is becoming increasingly prevalent in urban studies, with an assortment of applications (Üsküplü, Terzi, & Kartal, 2020). In fact, point of interest and social media check-in information are some of the most effective instruments for assessing urban landscape (Wu, 2022). McKenzie et al. (2015) for instance , proved the viability of utilizing a Foursquare database to convey temporal, thematic, and spatial distribution patterns (Padrón-Ávila& Hernández-Martín, 2017; Mondo et al., 2020).

In line with this approach, innovative research has improved the identification of Tourist Activity Centers using Foursquare, Twitter, Google Places, and Airbnb. Instances of these centers of attraction include Valencia and Alicante, Spain (Martí et al. 2021). According to Salas-Olmedo et al. (2018), innovation has also been achieved in the usage of LBSNs, especially Twitter, Foursquare, and Panoramio, to determine tourism activities from user-generated content in the context of Barcelona, Spain.

In spite of the developed benefits of LBSNs for locating points of interest (POIs) in urban areas, this study conveys a methodology for identifying and pinpointing tourist activity centers (TACs) by incorporating data from five distinct LBSNs: Twitter (Salas-Olmedo et al., 2018; Cebrián & Domenech, 2023), Instagram (Mondo et al., 2020), Instasights heatmaps (Avuxi Ldt 2024), Foursquare (Foursquare Inc. 2019), and TripAdvisor (TripAdvisor LLC 2022).

Firstly, Twitter is a social media network for micro blogging. It is one of the most prevalent sources because tweets enable free, geotagged, real-time information. (Encalada-Abarca et al., 2024), thus valuable information on the tourist footprint can potentially be retrieved from tweets and sender profiles (Yubero et al., 2021). Actually, using Twitter's API (application programming interface) is the primary method for obtaining data from the social media platform for scientific purposes (Provenzano et al., 2018; Sontayasara et al., 2021). Studies that primarily employ tweets as their source of data frequently concentrate on the content of the tweets (Willson et al., 2021; Sontayasara et al., 2021; Carvache-Franco et al., 2022). Nevertheless, several research additionally take into account tweet geo-tagged data (Bhatt and Pickering, 2021; Kim et al., 2021). Furthermore, other researches consider the number of likes, retweets, comments, and tweets as well as the time at which they are posted as significant sources of information (Kwok et al., 2022; Cebrián & Domenech, 2023).

Secondly, Cebrián and Domenech (2023) state that Instagram is a free online multimedia platform that allows people and businesses to publish images, videos, reels, and stories (Yubero et al.,2021). A variety of researchers concentrate on the content of the photos uploaded to the platform, including the colors (Yu & Egger, 2021; Yu et al., 2023) or the topic of the photograph (Aramendia-Muneta et al.,2021). Other studies integrate the image's attributes with different kinds of data, like the posts' geotagged data (Encalada-Abarca et al., 2024)

Thirdly, the Instasights heatmaps is an online tool created by Avuxi Top-Place heatmaps service; it offers an overview of the most popular visited areas within a city presented in easily comprehensible map overlays (Martí Ciriquián et al., 2019). It is updated daily and utilizes information on over 200 million places from more than 70 public sources (Avuxi Ltd 2024). The website, which provides informative maps throughout the world, is also accessible to the public (Nolasco-Cirugeda et al., 2022). Instasights heatmaps provide valuable insights into various aspects of urban tourism phenomena, including monitoring urban dynamics after public space renewal and pinpointing high concentrations of users within cities (Martí et al., 2021). Instasights cartographies illustrate four popular tourist activities: eating, shopping, sightseeing, and nightlife (Martí et al., 2021; Waiyausuri et al., 2023).

Fourthly, the LBSN that is check-in based foursquare encompasses a registry of socioeconomic activities and relevant locations in the city, known as venues (Foursquare Inc., 2019). By "checking-in" at a particular area, foursquare users may share not only their location but also their thoughts and experiences regarding that particular spot (Mondo et al., 2020). In tourism researches, Foursquare has also been used to rank preferences (Tammet et al., 2013) and identify popular tourist destinations or activities (Gao et al., 2024).

Fifthly, The TripAdvisor website stands out as a prominent platform for user-generated content, significantly impacting the decision-making process of prospective travelers (Nolasco-Cirugeda et al., 2022). Recent scholarly attention has been directed towards TripAdvisor as a valuable resource for investigating consumer behavior and preferences, encompassing a range of subjects, including the effects of market positioning (Mou, 2022), decision-making processes of travelers (Litvin & Dowling, 2018), and the impact of factors like accessibility and walkability on the spatial behavior of tourists (Hall & Ram, 2019).

Noteworthy, all these platforms have been employed in previous researches and proven to be appropriate contributors of baseline information to address a range of tourism-related issues (Mondo et al., 2020; Martí et al., 2021; Nolasco-Cirugeda et al., 2022; Cebrián & Domenech, 2023; Encalada-Abarca et al., 2024).

## Context of the study area: Alexandria city

Alexandria city is situated 210 km north of Cairo on the Mediterranean Sea. Its boundaries extend 70 km northwest along the coast from the Nile delta (World Bank Document, 2008). According to Hassan et al. (2023), Alexandria extends along the 171-kilometer Alexandria-Cairo desert route, reaching Abu Quir Bay and Edco Lake to the east, and El Hamam town at km 60 on the Alexandria-Matrouh highway to the west. Alexandria's strategic location on the Mediterranean Sea, which has given it historical and commercial popularity for centuries, is a contributing factor for its importance (Mohamed, 2023). Out of the 5.9 million people living in Alexandria, roughly 95 percent reside in the city itself, while the rest of the population residing in Burg Al Arab new town and the surrounding areas (Hassan et al., 2023). Alexandria is regarded as the most popular summer travel destination (Soliman & Soliman, 2022). It should be noted that a government report issued by the Tourism Office in the General Office of Alexandria Governorate stated that the number of foreign tourists who visited Alexandria city during the past year (2023) amounted to about 84,161 thousand, at a rate of 12%, followed by Arabs, 81,567 thousand, indicating that the number of Egyptians recorded about 540,118 thousand representing 77% of the total number (www.alexandria.gov.eg ).

Alexandria's city is motivated to develop the tourist industry because this sector enhances the city's overall prosperity (Benghadbane & Khries, 2020), produces more exports, and offers employment opportunities (Soliman & Soliman, 2022).

In this context, this city has been selected as extremely suitable case study for several reasons (Martí et al., 2021): a distinct historical position as a cosmopolitan city and cultural landmark; unique assets related to archaeology and cultural heritage that span multiple eras and form a rich urban fabric; and modern landmarks (World Bank Document, 2008). With the reconstruction of Bibliotheca Alexandrina attracting a million visitors annually, the city is being positioned as a regional center for knowledge, science, and intercultural dialogue (World Bank Document, 2008); it also boasts a well-established, rapidly expanding, and diverse manufacturing sector accounting for 40% of Egypt's industrial investments, employing roughly 30% of the local labor force in Alexandria (Hassan et al., 2023) and important transportation infrastructure. It also provides two of the country's top seaports, handling roughly 60% of the nation's imports and 47% of its exports; two international airports; and the capacity to further diversify its economic base in areas with significant but unrealized potential, like tourism (Alexandria remains the main local tourism destination, but only receives 3-5% of Egypt's international visitors each year).

Despite the outstanding contemporary tourist attractions that the city offers, the absence of a coherent state plan to promote the city as a travel destination unable the city to establish its own "image on the international tourism map" (Surugiu et al. 2020). In this line, according to the recent research conducted by Surugiu et al. (2020), Social media represents virtual, voluntary, and private city marketing, thus providing an essential instrument for evaluating tourist services. Accordingly, the analysis of Alexandria’s tourism realities based on social media data reveals evident opportunities, making this city an appropriate subject for case study (Martí et al., 2021).

## Sources and Methods

Notably, this study relies on a set of primary data sources, as well as several analytical methods and tools for data analysis. These have been summarized in the following tables:

**Table (1) Data source analysis and measurement tools**

| Data source analysis and measurement tools | Description |
|---|---|
| collaborative mapping | Citizen mapping, is the aggregation of Web mapping and user-generated content, from a group of individuals or entities, and can take several distinct forms. Volunteers collect geographic information and the individuals can be regarded as sensors within a geographical environment (Sangiambut & Sieber, 2016). |
| Voluntary geographic information (VGI) | Refers to geo-referenced data created by citizen volunteers. These dedicated individuals actively contribute geographic information |

| | |
|---|---|
| | (Martí Ciriquián et al., 2019). |
| Popularity scale | The more frequently users use a map, the more that map seems to meet their needs (Konstantinou et al., 2023). |
| Points of interest POI | Data provide digital representations of places in the real world which may be of interest to some population groups to enhance user experiences by providing detailed information about nearby places(Sun et al., 2023). |
| Spatial Vector map | A cutting-edge approach to mapping that leverages geospatial data to create dynamic and interactive maps in real-time. It using mathematical equations to render geospatial data in real time (Mapbox, 2024) |
| Spatial Heatmap | Displays the magnitude of a spatial phenomenon as color, usually cast over a map. In the image labeled "Spatial Heat Map Example," temperature is displayed by color range across a map of the world. Color ranges from blue to red (Wilkinson & Friendly, 2009). |
| Spatial analysis | A set of techniques for deriving new information and knowledge from spatial data. These techniques include all of the samplings, visualization, manipulation, and analytical methods that can be applied to spatial data(Hao, 2019). |
| Cluster analysis | Spatial clustering is a process of grouping a set of spatial objects into groups called clusters. Objects within a cluster show a high degree of similarity, whereas the clusters are as much dissimilar as possible (Neethu & Surendran, 2013). |
| Tourist activity Centers (TACs) | To identify Tourist Activity Centre areas – TAC areas – through LBSNs Heatmaps tool for pinpointing baseline areas with most tourism-related activity-i.e. sightseeing, shopping, eating and nightlife (Martí et al., 2021). |

One approach that proves to be highly effective in comprehending the collective perception of urban tourism is the utilization of collaborative maps to visualize the amalgamated image resulting from the contributions of diverse individuals. Therefore, the following table illustrates the primary sources for tourist map data and the geographic analysis tools used in the study.

**Table (2) Tourism Maps resources and geographic analysis tools**

| **Tourism Maps resources and geographic analysis tools** | **Technology** | **Provider** | **Type** | **Description** |
|---|---|---|---|---|
| **Geographic information system GIS** | | | | |
| **QGIS** | **application** | QGIS algorithm provider implements various analysis and geoprocessing operations using mostly only QGIS API. So almost all algorithms from this provider will work without any additional configuration | **General** | QGIS is a geographic information system (GIS) software that is free and open-source. It supports viewing, editing, printing, and analysis of geospatial data in a range of data formats. (QGIS, 2024) |

| | | | | |
|---|---|---|---|---|
| **Tourism Maps analysis tools** | | | | |
| **Avuxi Top place** | **Website** | **Map companies or VGI initiatives** | **General** | TopPlace™ analyzes geo-tagged Big Data from multiple sources to help uncover the social highlights of entire cities and neighborhoods, instantly highlighting what city areas are popular for what, whom and when.(avuxi, 2024) |
| **Flosm** | **Website** | **Map companies or VGI initiatives** | **General** | The Open Street Map POI Map In the POI map we visualize the "Points of Interest" that can be found in OSM data. From several hundred categories, you can get an overview of the variety of data and completeness of the OSM database worldwide. |
| **Instasight** | **Website and application** | **VGI initiatives** | **Tourist** | InstaSights uncovers the most popular places anywhere on Earth. The app helps to quickly find those great spots that have already been recognized by millions of locals and travelers (Instasight, 2024). |
| **Open Trip map OTM** | **Website and application** | **Map companies or VGI initiatives** | **Tourist** | A tool to collect and analysis information about tourist activities using Popularity scale and heatmaps analysis. (Opentripmap, 2024). |
| **Geo-located information based social networks** | | | | |
| **Foursquare** | **application** | **VGI initiatives** | **Tourist** | It provides personalized recommendations of places to go near a user's current location based on users' previous browsing history.(Kim, 2015) |
| **OmniSci Tweet map** | **website** | **VGI initiatives** | **General** | It is a (Graphics Processor Unit)-powered database and visualization platform designed for lightning-fast, immersive data exploration that excluded from X social media application. (heavyai, 2024) |
| **Instagram** | **Website and application** | **VGI initiatives** | **General** | Allows users to capture, create,and share moments with friends, fans, and brands.(Instagram, 2024) |

| Base layer of spatial maps | | | | |
|---|---|---|---|---|
| **Open street map OSM** | **Website and application** | **Map companies or VGI initiatives** | **General** | **OSM** is open data built by a community of mappers that contribute and maintain data about roads, trails, cafés, railway stations, all over the world. (OSM, 2024). |
| **Google map GM** | **Website and application** | **Map companies or VGI initiatives** | **General** | A web mapping platform and consumer application offered by Google. It offers satellite imagery, aerial photography, street maps, 360° interactive panoramic views of streets , real-time traffic conditions, and route planning for traveling by foot, car, bike, and public transportation. (Google Maps Metrics and Infographic, 2022) |

Based on the above, the contemporary perspective on collaborative mapping is regarded as a body of scholarly work centered on data sourced from user-generated content on social media platforms and location based services. This data comprises individual inputs that, when analyzed collectively, offer valuable insights into the perceived image of urban tourism, as indicated by existing research endeavors (Martí Ciriquián et al., 2019).

This particular tool serves the purpose of displaying vast amounts of Voluntary Geographic Information (VGI) data that have been collected and scrutinized from more than 60 distinct social media platforms. Consequently, heatmaps portray numerous individual perspectives on a city, emerging as a promising avenue for 'public maps' that are routinely updated, thereby reflecting the current urban landscape (Martí Ciriquián et al., 2019).

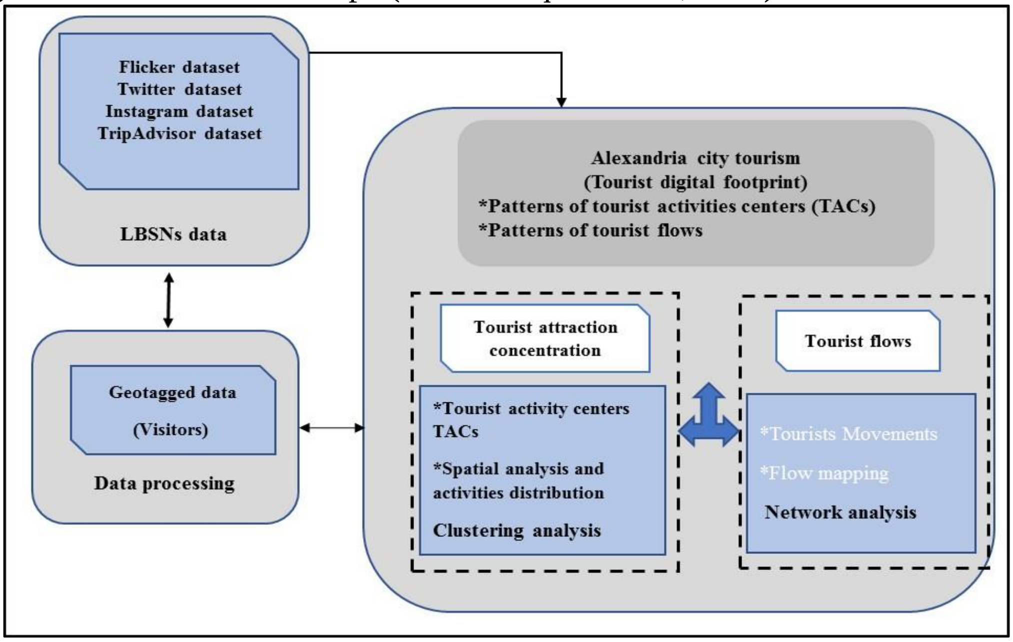


**Figure (1):** Analytical framework of Alexandria city digital foot print retrieved from LBSNs.
**Source:** Researchers' own

## Study sample

The study sample consists of both international and local visitors and tourists to tourist activities centers in Alexandria city. These visitors and tourists interact in various ways with location-based social networks. Some visitors may be virtual, engaging solely through electronic interactions without physically visiting the tourist activity center. Others interact both physically by visiting the center and electronically through various location-based digital media. Hence, the sample depends on the virtual and real-time presence of visitors and tourists, which reflects the density of movement.

## Procedures and results analysis

The practical study involves a set of procedural steps to achieve practical results as follow:

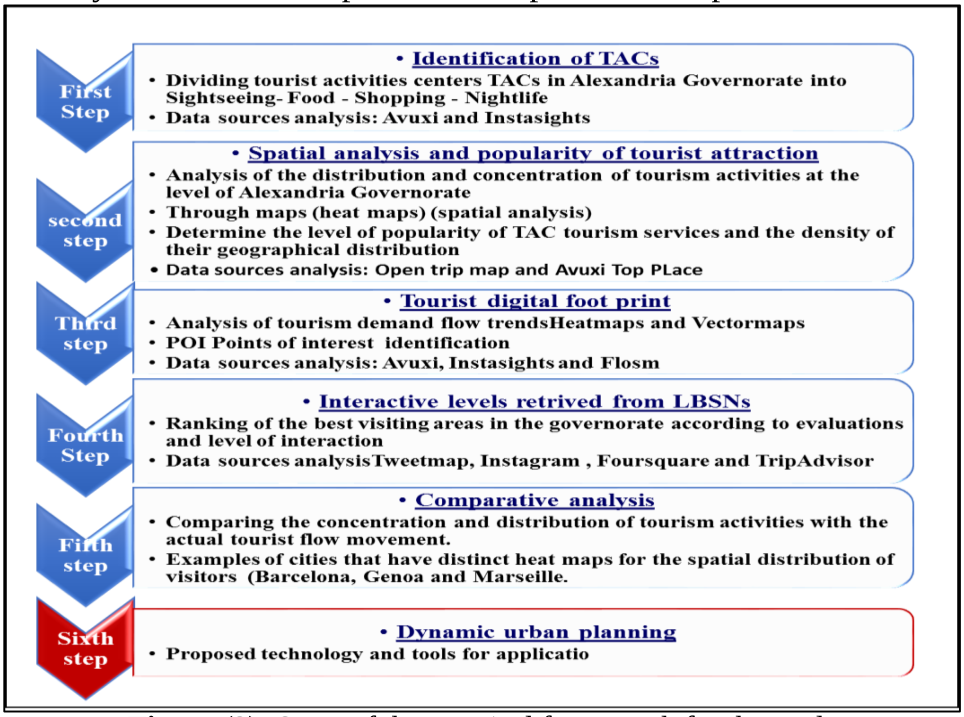


**Figure (2):** Steps of the practical framework for the study
**Source:** Researchers' own

## The first step: the identification of TACs

In an effort to determine the perceived functional thematic regions of the five tourist activity centers (TACs) in Alexandria city, a demo website of the AVUXI TopPlace Heatmaps service serves as a tool that aggregates and assesses 'billions of user-generated geotagged signals, regularly indexed across 60+ public sources', generating maps featuring a five-level color gradient (heatmaps) that depict data density, thereby unveiling the most frequented areas for each specific category.

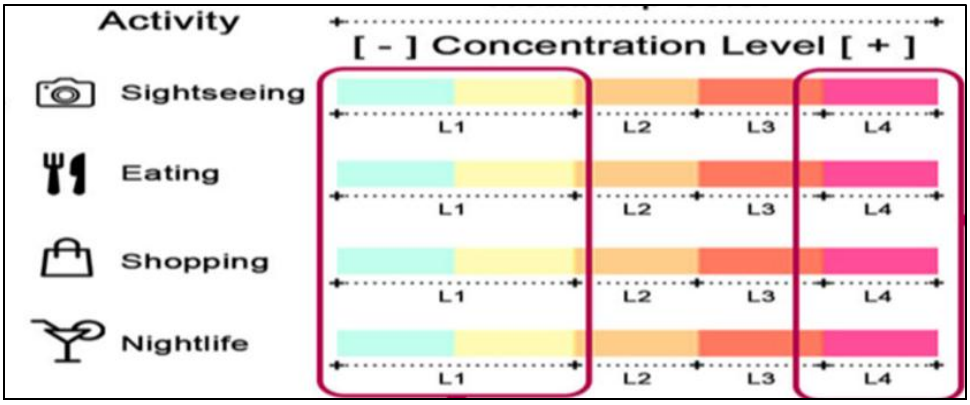


**Figure (3):** Heatmap color

**Source:** Researchers' own

A depiction of the AVUXI TopPlace's vector-shaped heatmaps, exhibiting the vector-shaped visualization for each of the four categories-sightseeing, shopping, eating, and nightlife-was generated for the case study city. These visual representations were imported into a GIS program-QGis, Prizren 3.32 version-and the gradient vector shapes at each heatmap level were meticulously outlined on the city's cartography. The resultant curvilinear forms were categorized by color according to the respective category and were assigned varying shades to denote the original gradient of the heatmap. The pink shade signifies areas with the highest concentration of geolocated inputs recorded for each category, thus revealing the whereabouts of the most popular regions.

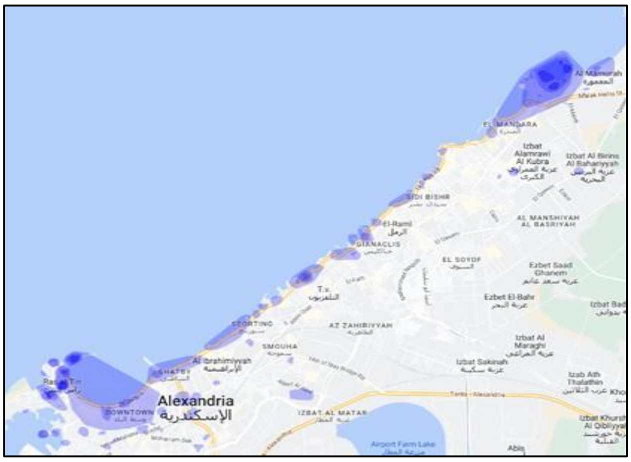


**Figure (4):**Locating the Tourist activities centers from Vector map

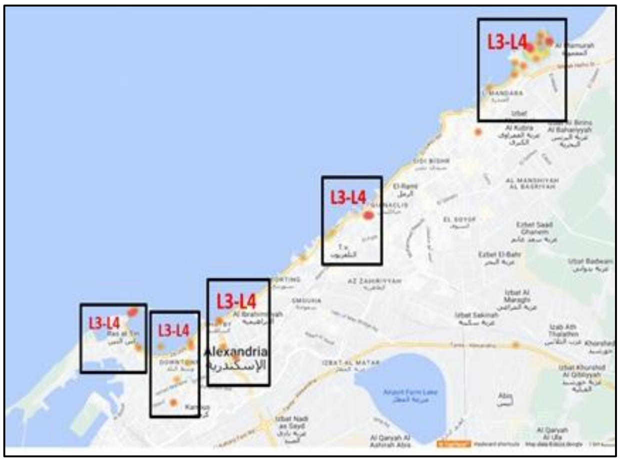


**Figure (5):**Locating the most concentrating tourism activities from heat maps

**Source:** authors own based on AVUXI Top Place with data analysis by QGIS

**TACs zones were chosen based on the subsequent criteria:**

- The primary zones of tourism activity in Alexandria city were identified in accordance with Avuxi application, which were integrated based on the color scale depicted in the heat maps. Zones with (L3-L4) concentration levels were included based on the heat mapping scale, while those with lower concentration, coded as (L1-L2), were omitted.
- Through spatial analysis of Vector heatmaps, tourist activity centers TACs in Alexandria city were determined, utilizing the Avuxi website for spatial data analysis.
- The central zones designated as hubs for tourism activity in the city encompass the four principal activities layers outlined in the study: Sightseeing, Eating, Shopping, and Nightlife.
- Consequently, areas within Alexandria city lacking this combination of activities were disregarded. Through spatial analysis, selection of representative TAC (R-TAC) areas defined as those with at least one centroid for each of the four activities.
- Additionally, the QGIS was employed to identify the most concentrated centroids of four tourism activities centers in Alexandria governorate.
- Five R-TAC areas were recognized for the focal points of tourism activities concentration in Alexandria: **A, B, C, D**, and **E**.

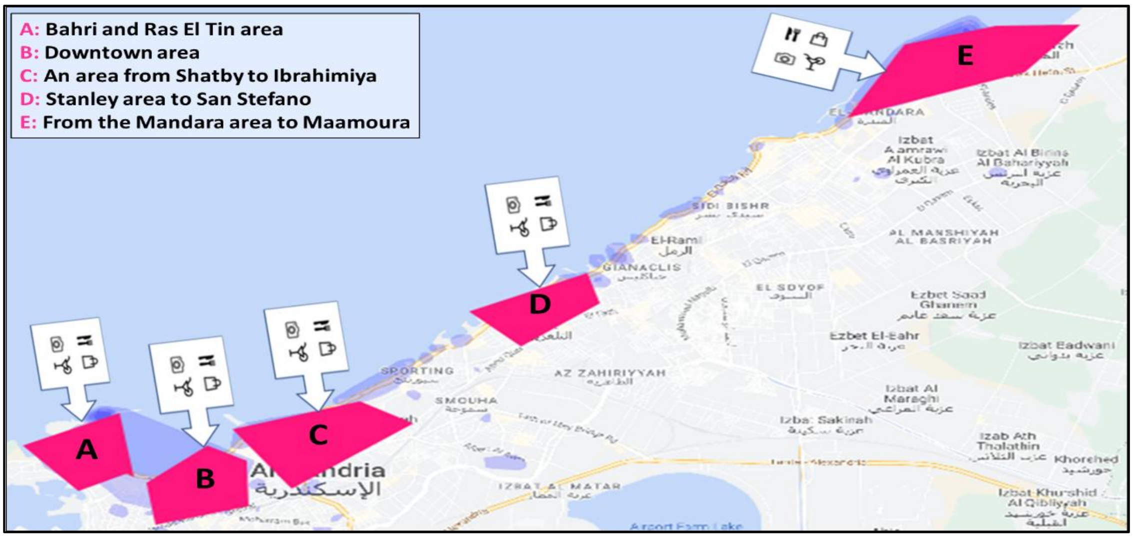


**Figure (6):** R-TACs in Alexandria city

**Source:** authors own based on AVUXI TopPlace with data analysis by QGIS

## The second step: spatial analysis and popularity of tourist attraction

By employing Open Trip Map and Avuxi Top Place application to analysis heat maps and spatial distribution of tourist attraction activities within the five designated areas (R-TACs) from the previous step, the analysis also utilized spatial clustering to deduce the outcomes of activity distribution and their spatial aggregation within the designated areas of the region by employing geographic information system (QGIS). **The ensuing outcomes were as follows**:

- The utilization of a popularity scale was employed to evaluate the five designated tourist activity centres TAC. This scale ranges from pinpointing the most renowned areas to encompassing both famous and lesser-known regions. It interprets fame levels based on social media interactions, discussions, visits, and engagement. As interest in a specific area grows, its fame increases, and vice versa. However, it’s essential to note that fame doesn’t necessarily reflect tourism flow trends. While an area may have significant social media fame, its actual tourist influx could be weak or low.

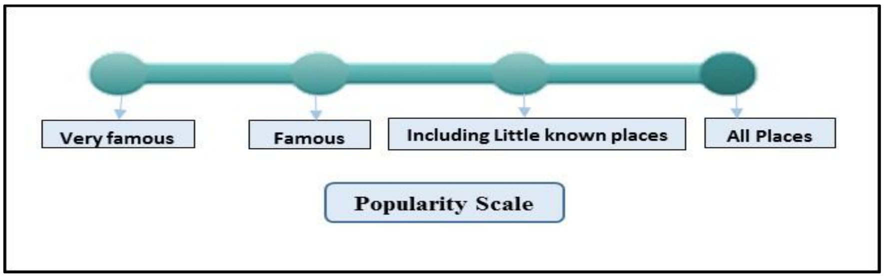


**Figure (7): Filter by popularity**

**Source:** Open trip map

- Upon analysing heat maps of tourist activity centers in Alexandria city, it becomes apparent that the popularity of tourist sites is notably low in comparison to the array of activities available across the five regions. Notably, when classifying the popularity rating as 'very famous', the heat maps exhibit limited coverage, indicative of the scarcity of renowned tourist spots within these zones, leading to a concentration of tourism activities within the city.
- Furthermore, the heat maps predominantly highlight three key areas - A, B, and E, underscoring the pronounced lack of popularity in central Alexandria's tourist locales.
- When considering the popularity rating encompassing 'all places', a widespread distribution of specific tourism ventures is observed within the concentrated tourist areas, highlighting the dearth of requisite information to stimulate tourism interest across the four identified

categories. Consequently, the expansion and diversification of tourism activities are evident throughout the entirety of the city.

- Additionally, a maximum travel time of 20 minutes to reach tourist attractions within a single tourist hub has been stipulated.


Figure (8):Heatmap of very Famous tourist activities Concentration in TACs

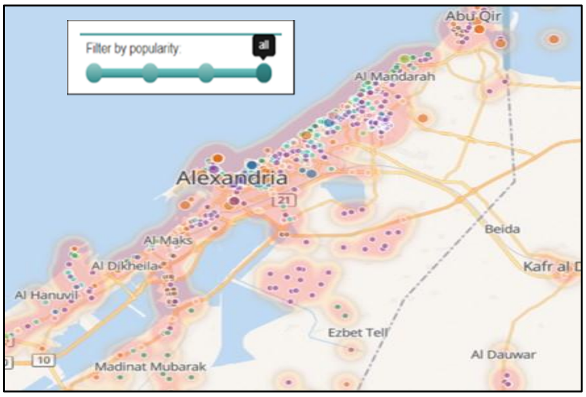


Figure (9):Heatmaps of all tourist activities Concentration in TACs

**Source:** authors own based on Open trip map with data analysis by QGIS


**Figure (10)**: Spatial analysis Map of area (A)

**Source:** authors own based on Open trip map with data analysis by QGIS

Through the cluster spatial analysis of the map of area (A), we notice a large distribution of tourist activities from the four categories at the level of the region as a whole when determining the level of popularity at “Very famous” on the popularity scale. The most Popularity areas in this region are Qaitbay Citadel, the Aquarium Museum, and Mursi Abul Abbas Mosque.


**Figure (11):** Spatial analysis Map of area (B)

**Source:** authors own based on Open trip map with data analysis by QGIS

Area (B) is considered one of the areas that contain the most diversity and spread of tourist activities at the level of the four categories (sightseeing, eating, nightlife, and shopping). The most concentrated attractions in this area are the cemeteries of Kom el Shoqafa, the Alexandria National Museum, and the Opera House.


**Figure (12):** Spatial analysis Map of area (C**)**

**Source:** authors own based on Open trip map with data analysis by QGIS

While area (C) represents a moderate and balanced area in the distribution of tourist activities, as we notice a significant balance between the four tourist activities, but among the main attractions according to the spatial analysis are the Library of Alexandria, the Shatby Casino, and El-Shalalat area.


**Figure (13):** Spatial analysis Map of area (D)

**Source:** authors own based on Open trip map with data analysis by QGIS

We also note that area (D) is dominated by shopping activities, nightlife, and restaurants, and there are a number of important tourist attractions such as the Royal Jewelry Museum and the Tombs of Mostafa Kamel.


**Figure (14):** Spatial analysis map of area (E**)**

**Source:** authors own based on Open trip map with data analysis by QGIS

Through Cluster analysis of area (E) and Heatmap Analysis, we notice a large and diverse spread of tourism activities in this region, which are mainly concentrated in the special attractions of Montazah Gardens and Maamoura Beach.

**Table (3) Percentage of Tourist activities Concentration within TAC areas**

| Area | Percentage of Tourist activities Concentration | Distribution of activity within TAC areas | | | |
|---|---|---|---|---|---|
| | | Sightseeing | Eating | Shopping | Nightlife |
| B | 32% | *** | ** | *** | ** |
| C | 27% | ** | ** | * | ** |
| D | 18% | ** | *** | *** | *** |
| A | 14% | *** | *** | * | ** |
| E | 9% | *** | ** | ** | *** |

**Source:** QGIS Cluster Spatial analysis for tourist activities heatmaps

The table (3) illustrates the concentration percentage of tourist activities in the five main tourist centers. It also indicates the relative importance of each tourist activity within these centers.

**The scale is as follows:**

- **One-star symbol * :** Indicates the least concentration of tourist activities.
- **Two-star symbol **:** Indicates moderate concentration for each tourist activity.
- **Three-star symbol *** :**Indicates high concentration for each tourist activity.

This information accordingly helps identify key tourism spots and guide visitors to active and exciting areas in the region. Local governments can benefit from this data to improve policy direction and plan for tourism sector development.

## The third step: tourist digital foot print

Through the examination of heat maps generated by the Open trip map tool and the utilization of the QGIS software for conducting spatial analysis on these maps, an observation can be made regarding the uneven distribution of tourist flow trends within the five tourist centers in Alexandria. It is evident that the greatest tourist flow is observed in Area **(E)**, with Area **(B)** closely following suit, as indicated by the magnitude of heat distributions within the map.

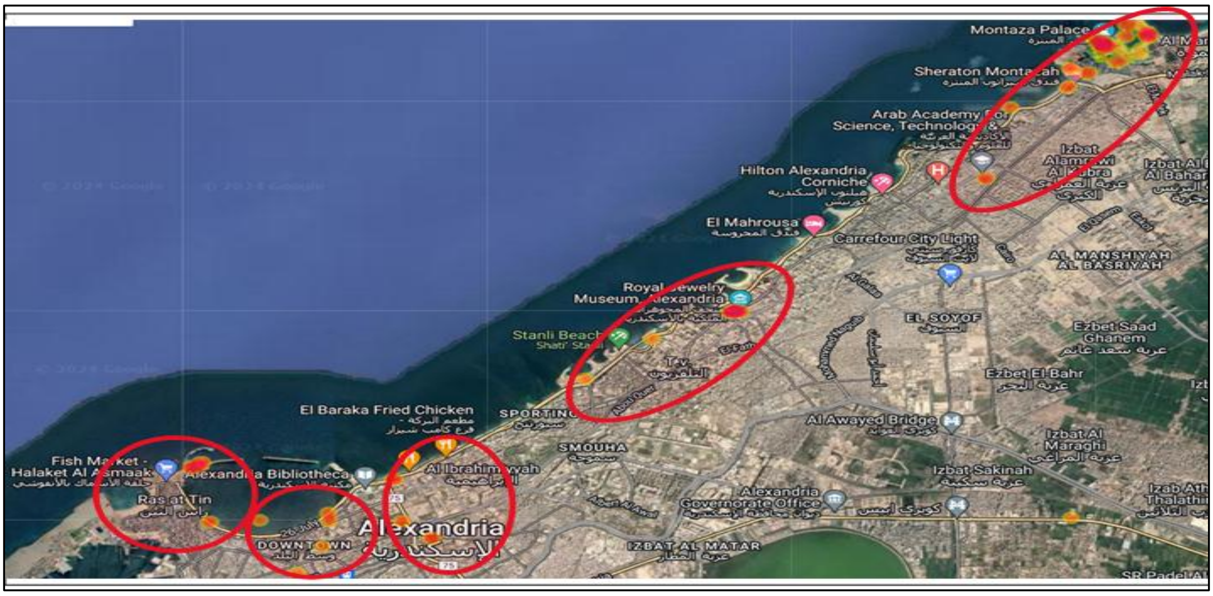


**Figure (15):** A compiled heatmap of tourist flow movement in tourist activity centers TACs

**Source**: authors own based on Avuxi Top place with data analysis by QGIS

**Figure (16):** Heatmap of tourist flow in area (A**)**

**Source**: authors own based on Avuxi Top place with data analysis by QGIS

Examination of the heatmap depicting the distribution of tourist movements within Area (A) reveals a notable concentration of tourism activity in the Qaytbay Fort region and the Aquarium, as well as at the Morsi Abu Abbas Mosque and the Farooq coffee vicinity. Conversely, the remaining tourist sites within Area (A )experience significantly lower levels of tourist flow.

**Figure (17):** Heatmap of tourist flow in area (B**)**

**Source:** authors own based on Avuxi Top place with data analysis by QGIS

Analysis of the heat map for Area (B) reveals the distribution of tourism activity across the entire region. The primary hubs of tourist influx are concentrated around the Raml station vicinity, featuring various shopping destinations. Additionally, notable tourist attractions such as the Roman Theater and the Qaid Ibrahim Mosque also attract significant tourists flow. Conversely, the tombs of Kom Al-Shoqafa and the Greco-Roman Museum exhibit below-average foot print, as indicated by the light blue shading on the heat map.

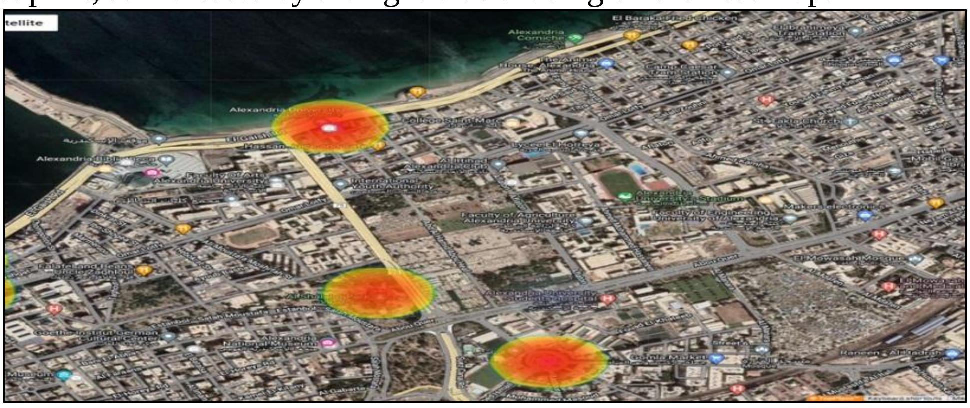

**Figure (18):** Heatmap of tourist flow in area (C**)**

**Source:** authors own based on Avuxi Top place with data analysis by QGIS

In Area (C), the examination of heatmaps indicates that it is regarded as one of the least active regions in terms of tourism demand within Alexandria city, despite hosting a wide array of tourist attractions. Tourist flow is primarily concentrated around the Library of Alexandria, the Shalalat area, and the stadium area. Nevertheless, the highest influx of tourists is observed specifically in the proximity of the Library of Alexandria.

**Figure (19):** Heatmap of tourist flow in area (D**)**

**Source:** authors own based on Avuxi Top place with data analysis by QGIS

The heat map of Area (D) reveals that it experiences the lowest flow of tourists compared to other areas. This is evident in the predominant color spectrum of yellow and blue tones representing tourist activities in this region. Notably, there is a significant tourist presence at the Royal Jewelry Museum and San Stefano Mall, while tourist traffic is less pronounced around Golden jewel Beach and Stanley Bridge.

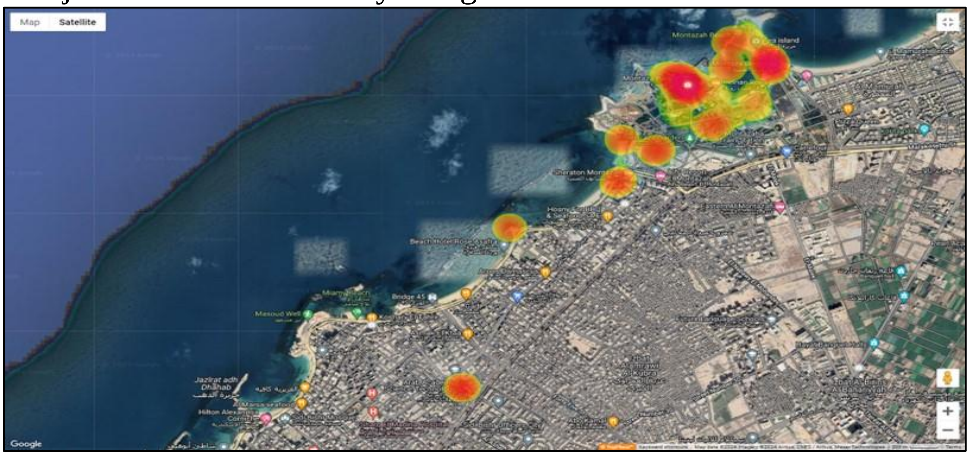

**Figure (20):** Heatmap of tourist flow in area (E**)**

**Source:** Authors own based on Avuxi Top place with data analysis by QGIS

Based on the provided information, it appears that the E region on the heat map experiences higher tourist activity. This is evident from the red-shaded hotspots, which indicate greater movement in this area. Tourist activity is distributed between the EL-Montazah area and the Maamoura area. Additionally, there is lower activity density around the Sheraton Montazah Hotel and El Asafra Beach .

**Table (4): Percentage of Tourists flow footprint within TAC areas**

| Area | Percentage of Tourists flow footprint | Distribution of tourist flow within TAC areas | | | |
|---|---|---|---|---|---|
| | | Sightseeing | Eating | Shopping | Nightlife |
| E | 31% | *** | * | * | * |
| B | 27% | * | ** | *** | * |
| A | 21% | * | ** | * | * |
| C | 13% | ** | * | * | * |
| D | 8% | * | ** | ** | ** |

**Source:** QGIS Cluster Spatial analysis for tourists flow heatmaps

Through the table (4) that illustrates the percentage of tourist flow at the level of major tourist centers, the importance of current tourist activities in each center becomes evident. The scale is as follows:

- **Three-star symbol *****: Indicates that the center is highly important for tourist flow.
- **Two-star symbol **** Indicates that the center has moderate importance for local tourist flow.
- **One-star symbol * :** Indicates that the center is of low importance for current tourist activity in the tourism concentration area.

This information helps identify key tourism spots and guide visitors to active and exciting areas in the region. Therefore, tourists can use this data to plan their trips and choose suitable places based on their interests.

## Identification of Points of interest (POIs)

Points of interest (POI) refer to a location that has a special interest for a particular purpose. POIs can be a Sightseeing, Nightlife, Shopping, or Eating. In the tourism industry, POIs can be used as reference points for visitors and provide detailed information related to the attractions.


**Figure (21)**: POIs map in Alexandria city
**Source:** https://www.flosm.org/en/

The analysis of points of interest in the five main tourist centers relied on the website www.flosm.org. This site utilizes the fundamental maps from the Open Street Map (OSM) program. Data is collected from various Location-Based Social Networks (LBSNs). The map data was updated until the end of March 2024. It significantly illustrates the distribution of most points of interest across the entire Alexandria city. However, it’s essential to note that this data heavily relies on user interactions with the OSM map. Points of interest may not necessarily reflect the actual demand for these locations but could result from electronic interactions with the map.

Based on the analysis of data related to points of interest, it becomes evident that they do not align at all with the flow of tourist demand. This discrepancy highlights an imbalance between the distribution of points of interest and the actual tourist movement within the five main centers of tourist activities, underscoring the need to implement the appropriate urban planning policies in the city.

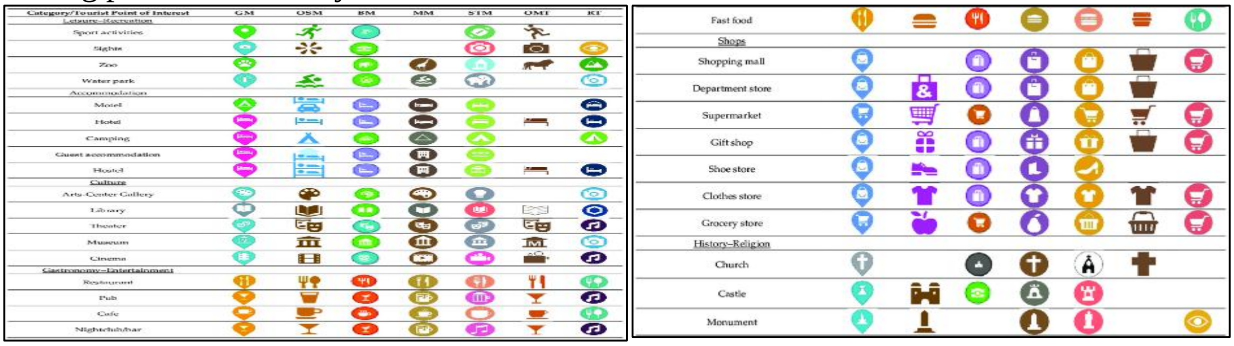


**Figure (22):** POIs Symbols

**Source**: Konstantinou, E. N., Skopeliti, A., & Nakos, B. (2023). POI Symbol Design in Web Cartography- A Comparative Study. ISPRS International Journal of Geo-Information, 12(7), 254.

## The fourth step: Interactive levels retrieved from LBSNs

Initially, this part will shed light on the ranking of the most visited areas in Alexandria according to ratings and level of interaction using Tweetmap, Instagram, Foursquare, and TripAdvisor:

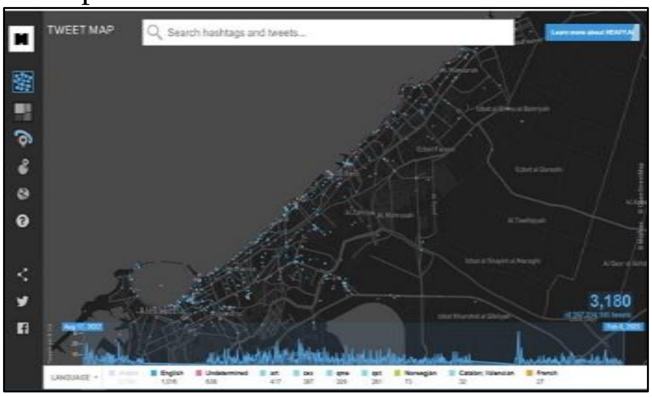


**Figure (23):** Distribution of tourist Tweets in Alexandria map

**Source:** authors own based on Tweet map


**Figure (24):** Most visited attractions in Alexandria by Foursquare users

**Source:** authors own based on Foursquare


**Figure (25):** Most visited attractions in Alexandria by TripAdvisor users

**Source:** authors own based on TripAdvisor users


**Figure (26):** Most visited attractions in Alexandria by Instagram users

**Source:** authors own based on Instagram users

Through an examination of the analytical maps generated by Location-Based Social Networks (LBSNs) such as Tweetmap, Instagram, TripAdvisor, and Foursquare, it can be deduced that there exist 15 common tourist destinations that are favored by the majority of users on social media platforms in Alexandria city. It should be noted that all of these attractions fall within the Tourist Attraction Clusters (TACs) that were identified during the initial step.

**Table (5): Top 15 attraction centers in Alexandria according to LBSNs users' reviews**

| Top fifteen attraction centers in Alexandria city | Reviews of LBSNs Users | | | |
|---|---|---|---|---|
| | Trip advisor | Foursquare | Tweet map | Instagram |
| | Number of review* | Number of reviews * | Number of tweets from 17August 2022 to 8 Feb 2023 | Number of posts* |
| Bibliotheca Alexandrina (area C) | 1861 Travelers' Choice award | 410 | 921 | 62.4k |
| Citadel of Qaitbey (area A) | 1123 Travelers' Choice award | 424 | 742 | 24.1k |
| Catacombs of Kom el Shoqafa (area B) | 747 Travelers' Choice award | 34 | 621 | 5000+ |
| Montazah Gardens (area E) | 925 | 403 | 937 | 65.1k |
| Royal Jewelry Museum (area D) | 223 | 49 | 372 | 17.8k |
| Ancient Roman Amphitheater (area B) | 442 | 41 | 398 | 1000+ |
| Alexandria National Museum (area C) | 292 | 37 | 319 | 1000+ |
| Stanley Bridge (area D) | 573 | 23 | 483 | 21k |
| Mosque of Abu al-Abbas al-Mursi (area A) | 173 | 7 | 188 | 500+ |
| Pompey's Pilla (area B) | 504 | 50 | 427 | 5000+ |
| Alexandria Opera House (area B) | 22 | 67 | 142 | 1000+ |
| Al-Raml station (area B) | 38 | 210 | 1184 | 23.2k |
| San Stefano mall (area D) | 8 | 737 | 887 | 32.3k |
| Gleembay (area D) | 134 | 58 | 901 | 180k |
| Elmaamora (area E) | 89 | 31 | 662 | 40.9k |

* **Data has been gathered progressively since the inception of the incorporation of tourist sites into the initiative, along with the initial assessment of user experiences at these sites.**

The results of the analysis, whether in the form of maps or visitor data from these platforms, consistently align with the findings from the preceding stages, and that is as follows:

- Regarding Area (A), the interactions of LBSN users predominantly revolve around Qaitbay Castle and its vicinity, with comparatively less attention being given to Al-Mursi Abu Abbas Mosque and the surrounding area.
- Area (B) stands out as a location with a high concentration of diverse tourist spots that have captured the interest of visitors and social media users alike, either through physical visits, online discussions, or reviews, claiming 5 out of the 15 highlighted attractions.

- In relation to Area (C), the majority of visits were centered on a single site, the Library of Alexandria, which emerged on top in terms of ratings, visitation numbers, and overall popularity as one of the premier tourist destinations in Alexandria.
- Area (D) witnessed a significant influx of tourists engaging in dining and shopping activities, particularly evident in the bustling Gleem Bay area and San Stefano Mall, while the Royal Jewelry Museum experienced below-average footfall.
- As for Area (E), the focus was predominantly on Ma'amoura and Montazah Gardens, with no other points of interest being featured within this particular zone.

## The fifth step: Comparative analysis

Through the integration of spatial data from Avuxi, Open Trip Map, and the spatial analysis conducted using QGIS, an examination reveals an imbalanced distribution of heat maps depicting tourists flow concentrations in comparison to the actual distribution of tourism activities across the five identified tourist activity centers. It is evident that the locations of tourist activities, indicated by blue points, are notably distant from the heat spots representing the tourists flow distribution, highlighting an uneven allocation of tourist congestion within and among these centers.


**Figure (27):** A map showing a comparison between the flow of tourists and the distribution points of tourist activities

**Source:** authors own based on Avuxi Top place and Open trip map with data analysis by QGIS

This necessitates the development of strategies to better align urban tourist flow with the diverse range of activities and attractions available at the identified tourist activity centers. Such efforts aim to alleviate congestion in certain areas while promoting equitable access to other regions and activities.

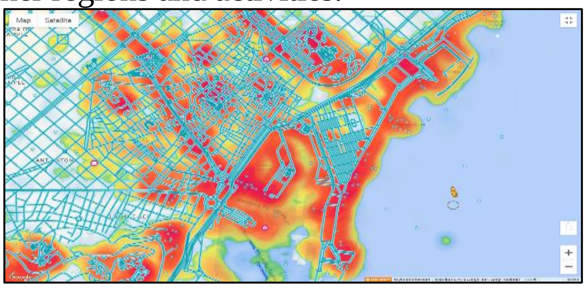

**Figure (28):** Tourists flow and tourism attractions heatmap for Barcelona

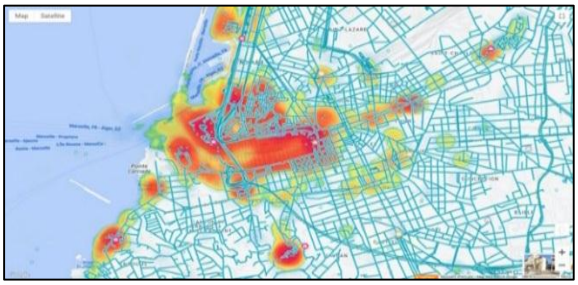

**Figure (29):** Tourists flow and tourism attractions heatmap for Marseille

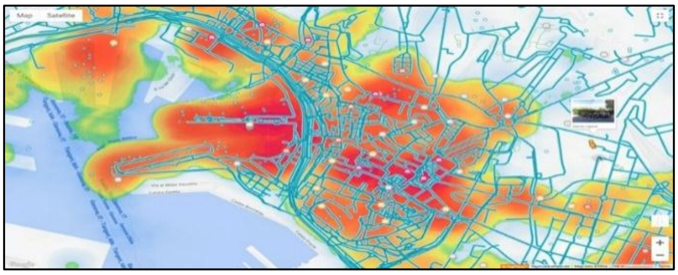

**Figure (30):** Tourists flow and tourist attractions Heatmap for Genoa
**Source:** authors own based on Avuxi Top place and Open trip map with data analysis by QGIS

## Distinctive international models for urban tourism patterns in coastal tourist cities

The heat maps for three of the largest coastal tourist cities in the world-Barcelona, Marseille, and Genoa-have been carefully selected. These heat maps are characterized by a balance between tourist movement distribution and the concentration of tourist activities. Consequently, these cities serve as distinctive models for urban tourism patterns, which could be applied to Alexandria city.

By comparing various heat map models for these tourist cities, we observe that the heat spots representing tourist movement are significantly aligned with the distribution of tourist activities. This alignment is evident through the broad coverage and interconnectedness of the heat spots, signifying the dispersion of tourist movement across most of the tourist attractions in these cities. Additionally, a majority of the blue points are situated within the thermal areas, indicating the effectiveness of consistency and integration between tourist flows and the utilization of key tourist activity centers in these cities. In contrast, the heat mapping of Alexandria city reveals isolated and diminutive heat zones. This reflects the fragmented nature of tourists' flow, with concentration occurring in specific areas while other regions receive less attention, which requires focusing on measures for equitable planning and restructuring of tourist areas.

## The sixth step: Dynamic urban Planning (AI proposed interaction technology and tools)

Dynamic urban tourism planning is a planning method that has the ability to capture the dynamic behavior of a complex system of tourism activity in the city over time (Group, 2021). It is critical to address the changing needs of tourists who visit cities and towns (Sedarati, 2019).

In this context, the dynamic urban planning approach can be utilized as a flexible method to swiftly and effectively address the proposed plans for managing tourist destinations. It allows for rapid responsiveness and a balance between tourist flow and tourist activity centers in Alexandria city. As a result, tourists can enjoy a comfortable and pleasant experience, avoiding overcrowding. Additionally, this approach generates tourist demand in centers and areas that may not have previously enjoyed significant tourism recognition.

Efficient management of tourist destinations is crucial to ensuring memorable and sustainable experiences for travelers and local communities alike**.** In fact, Artificial Intelligence is being used to collect and analyze real-time data on tourist flows, tourist attractions availability, transportation availability, and other relevant factors, enabling tourist destinations to make informed and proactive decisions to manage visitor flows, avoid congestion, and enhance the quality of the tourist experience (Garcia Madurga et al., 2023) .

Accordingly, the contents of the following table No (6) can indeed be used to assist the presentation of a proposal for the planning of tourism programs and itineraries leveraging artificial intelligence tools.

**Table (6) Proposed route planning based on AI technologies**

| Proposed technologies | Description | Tool examples |
|---|---|---|
| **Real time map based on LBSNs** | This expression refers to a process of map making for a level of computer responsiveness that a user senses as sufficiently immediate or that enables the computer to keep up with the georeferencing process (Karimi, 2009). | -Zone atlas<br>-Avuxi Top place<br>-Open trip map |
| **AI Based Tour Management System** | To provide a solution that is feasible and user-friendly for the management and planning of tour/vacation. Recommend and suggest various options needed for travel arrangements that are relatively convenient to the user. Provide the user with the basic requirements ideology of planning a tour and budget. Give a better understanding about the place that the user is going to visit to avoid confusion and chaos. Preplanned, transparent and handy notifications of the next task that is assigned. Suggest, schedule and book various means of transport and accommodations (Sadhana Singh et al., 2024). | -tripplanner.ai<br>-iplan.ai<br>-Plantrip.io<br>-https://copilot2trip.com/ |
| **Integration tourism solutions based on AI (TOMI )** | TOMI is an interactive urban solution that delivers all information that matters in the right place at the right time. Furthermore, TOMI's goal is to bring cities closer to people who live, work and travel in it. It is very innovative, user-friendly and a unique way to promote multiple activities and points of interest such as touristic, cultural, local commerce, public services among others.<br>The integrated solutions provide suitable trips for visitors in terms of time, cost, and preferences. Additionally, they offer real-time information on tourist flow to destination managers. Thus, they serve as both inputs and outputs for information simultaneously | **- TOMI** an interactive kiosk in tourist cities.<br><br>**-TOMI** application |

In summary**,** the idea of utilizing real-time updated tourist maps through momentary data provided by Location-Based Social Networks (LBSNs) is derived from the concept of dynamic urban planning. This flexible approach allows for swift and effective handling of proposed plans related to managing tourist destinations. By incorporating artificial intelligence technology, detailed tourist programs can be designed and implemented. These programs align with the principles of dynamic urban planning for tourist activity centers, enabling them to adapt to rapid changes in tourist demand in Alexandria city. The benefits of this approach include:

- **Creating Unique and Unconventional Tourist Routes**: Designing paths that cater to diverse visitor needs.
- **Providing a Comfortable and Enjoyable Tourist Experience, Minimizing Overcrowding**: Efficiently directing tourist flow to avoid congestion.
- **Balanced Tourist Planning for Destinations**: Monitoring and interacting with key tourist activity centers using real-time and updated data.
- **Maximizing Tourism Impact across the Entire city**: Distributing tourist movement evenly across various attractions in Alexandria, which means both spatially and temporally balance.
- **Predictive Analytics with algorithms analyze data** enabling destination management organization to identify patterns, trends, and insights in tourism demand**.**

- **Providing Guide Policy** to implement strategies that can assist in informing DMOs in advance of developing concerns about over tourism and enable them to plan accordingly with local businesses to redirect tourists to less-visited locations or simplify peak hours (Yigitcanlar et al., 2020). This would enable DMOs to adjust regulations and collaborate with companies to promote their products before irreparable damage to their reputation and image.

Thus, this approach serves as a complementary tool for sustainable urban planning decision-making in tourism and promotes the path towards responsible AI. To fully harness generative AI, datasets about travellers, residents, businesses and infrastructure must be standardized. Here, it should be noted that ethics should be integrated into artificial intelligence systems to enhance the lives of residents and visitors if managed carefully. With proper coordination, generative AI can redistribute tourists geographically and temporally to promote and ensure sustainable destinations (Yigitcanlar et al., 2021).

## Discussion and conclusion

The presented study reveals the difficulty of identifying tourism activities in cities (Martí et al., 2021).The method proposed in this study relied on analyzing the concentration of tourism activities in cities to provide a greater vision of the functional complexity of urban areas.

In line with earlier studies, the present research addressed the findings of Salas-Olmedo et al. (2018) and Martí et al. (2021), which suggested that many sources should be considered in conjunction when appraising the concentration of tourism-related activities and their urban spatial patterns can be portrayed in a way that incorporates user experiences and opinions into account through the use of LBSNs (as data sources). Additionally, the results support and validate other studies that contend Big Data derived from UGC provides a multitude of opportunities for addressing tourism-related phenomena (Martí Ciriquián et al., 2019; Gao et al., 2024). In particular, the reference framework provides different forms of analysis-spatial, clustering, and network-for identifying and analyzing TAC areas according to their functional variety.

The findings reveal that specific tourism-related dynamics and points of interest may be identified using the analysis and interpretation of LBSN data. Based on the study's findings Silva et al.(2018), it is evident that future research could profit from incorporating the analysis of spatiotemporal trends and tourist flow patterns throughout the day, week, or particular time period once R-TAC areas have been identified and particular points of interest have been highlighted.

Significantly, the study has prominently shown the suitability of the method used and delivered from various types of UGC sources. In particular, the Instasights Heatmaps website serves as a useful tool for identifying efficient baseline areas for four functional activities: eating, shopping, sightseeing, and nightlife. The Instasights Heatmaps website is one such source of UGC. This is a valuable resource for the field of urban studies for three main reasons: (1) it facilitates the identification and analysis of the tourist activity pulse by defining specific target areas to concentrate on; (2) it offers a tool for analysis that is open to all researchers and can potentially be replicated in any urban setting; and (3) it is a dynamic source as it is updated frequently. Furthermore, the choice of sources for LBSNs that provide a sample of user preferences and usage of urban areas enhances the findings of research, particularly those pertaining to urban planning (Salas-Olmedo et al., 2018).

**Focusing on the key findings in relation to our proposed research Alexandria city case study**, **the first observation in relation to the TAC areas is that their size is not proportional to that of the city**. Five R-TAC areas were recognized for the focal points of tourism activities concentration in Alexandria: A, B, C, D, and E. Interestingly, the Alexandria City case study revealed the emergence of many TAC areas; however, not all of them adjust inside the TAC area delimitation when the centroids, or largest concentration of a specific activity, were located. That was specifically one of the main factors taken into account while determining the R-TAC regions for this study, which are TAC case study areas. These were the only TAC places where the major centers of the four activities-eating, shopping, sightseeing, and nightlife-converged.

In addition to the above, the utilization of a popularity scale was employed to evaluate the five designated tourist activity centers TAC. **It became clear, through tracking and analyzing heat maps of tourist activity centers in Alexandria city that the popularity of tourist sites is significantly low compared to the range of activities available in the five main identified regions.** Moreover, heat maps mostly highlight three main areas - A, B, and E, which confirms the clear lack of popularity in the tourist areas in the central areas of Alexandria, which confirms the spread of diverse tourist activities in the city of Alexandria along the coastal strip and inland. While these various tourist activities and attractions may be unexploited or not marketed in proportion to their value and tourism importance.

Through the examination of heat maps generated by the Open trip map tool and the utilization of the QGIS software for conducting spatial analysis on these maps, **an observation can be made regarding the uneven distribution of tourist flow trends within the five tourist centers in Alexandria.** It is evident that the greatest tourist flow is observed in Area B especially around the Raml station vicinity, featuring various shopping destinations, and Area E which indicates greater movement as tourist activity is distributed between the EL-Montazah area and the Maamoura area. Hence, these informations have an essential role in identify key tourist sites and direct visitors to active and exciting areas in the region. Therefore, tourists can use these data to plan their trips according to the available times away from peak tourist times, as well as choose appropriate places based on their interests.

Moreover, based on the analysis of data related to points of interest, it becomes evident that they do not align at all with the flow of tourist demand. **This discrepancy highlights an imbalance between the distribution of points of interest and the actual tourist movement within the five main centers of tourist activities.**

These digital footprints demonstrate that the urban activity within the R-TAC areas is not homogeneous in terms of intensity, type, or spatial distribution, which necessitates the adoption of appropriate measures at the destination management organization level, by improving the construction of the tourism transport network and enhancing tourist accessibility for the city's tourist attractions.

In conclusion, The results of the spatial analysis conducted using QGIS also reveal an unbalanced distribution of heat maps depicting tourist flow concentrations compared to the actual distribution of tourist activities across the five identified tourist centers, which highlights an uneven distribution of tourist crowding within and between these centers. This requires the development of strategies to better align urban tourism flow with the variety of activities and attractions available in specific tourism activity centers to relieve congestion in certain areas while promoting equitable access to other areas and activities.

Overall, the scoping out of urban tourist activity pulse in Alexandria city , the monitoring of tourist digital foot print by using UGC sources and the adaptation of dynamic urban tourism planning based on responsible AI sources are the main contribution of this study.

The findings of this study have **significant implications** for tourism destination managers, urban planners and scientists interested in the analysis of urban dynamics. **A proposed framework** could be utilized as a flexible method to swiftly and effectively address the proposed plans for managing tourist destinations. It allows for rapid responsiveness and a balance between tourist flow and tourist activity centers. By incorporating artificial intelligence technology, real-time updated tourist maps through momentary data provided by Location-Based Social Networks (LBSNs) and detailed tourist programs can be designed and implemented. These programs align with the principles of dynamic urban planning approach for tourist activity centers. This contributes to the creation of unique and unconventional tourist itineraries that meet the diverse needs of visitors based on the mechanism of balanced tourism planning for destinations using real-time and updated data, to avoid problems of congestion and achieve temporal and spatial balance through the equitable distribution of tourist flow across the various regions Attractions. Finally, this approach serves as a complementary tool for sustainable urban planning decision-making in the field of tourism and advances the path towards responsible artificial intelligence.

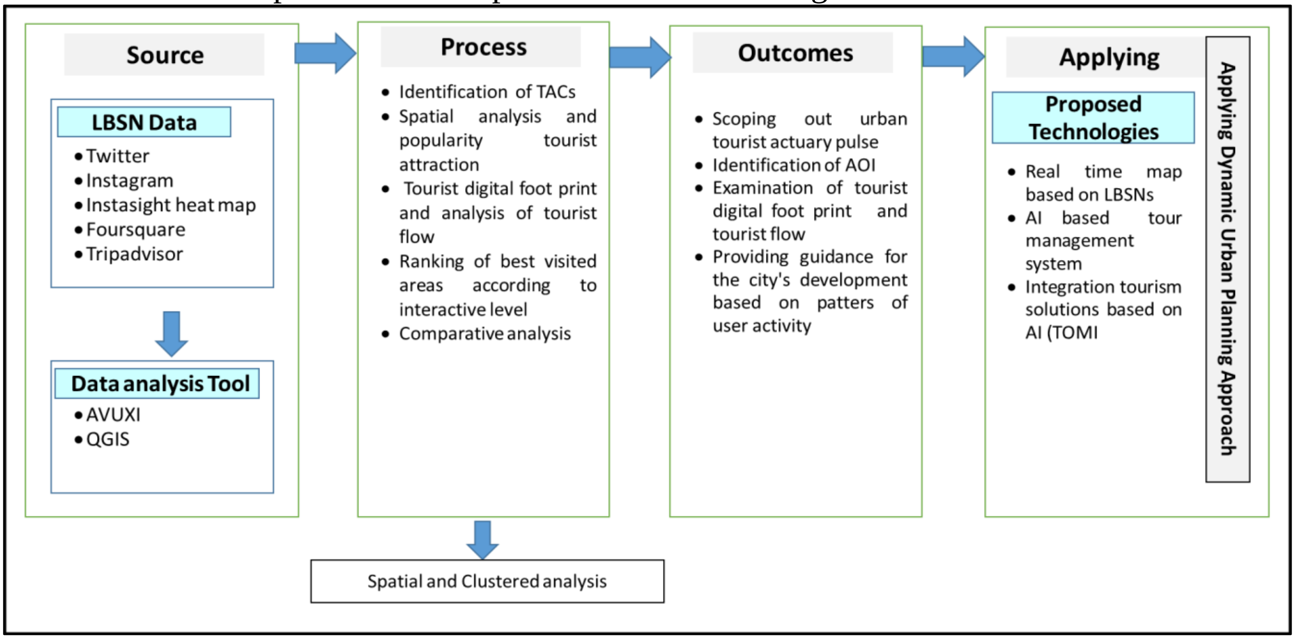


**Figure (31): The proposed dynamic planning framework (AI Tools and technologies)**
**Source:** researchers based on Martí et al. (2021); Yigitcanlar et al., (2021)

**The current study has some limitations**. The research is based on a single case study of Alexandria Egypt. Therefore, future research could take a large sample of various destinations into consideration. Additionally, further discussion is needed to conduct research on tourists' spatial behavior pattern and tourism experience analysis by integrating multi-source data types such as videos and images and studying the spatial and temporal data mining technology of the Geographic Information System.

Moreover, the possibility of applying the study methodology used in the future to the areas that were excluded in this study, as it includes centroids without diversity of activity, with the possibility of exploring the interconnections between the city's various TAC areas to reach areas that express the possibility of increasing urban dynamism at the city level.

Finally, using and integrating modern technological mechanisms that rely on real time techniques, taking into account the application of the principles of responsible AI planning (Yigitcanlar et al., 2020) to confront a number of issues such as over tourism and the spatiotemporal congestion patterns (Yigitcanlar et al., 2021)

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# رصد البصمة الرقمية السياحية ومراكز الأنشطة السياحية من خلال بيانات التوسيم الجغرافي والبيانات المحددة للموقع: مدينة الإسكندرية كدراسة حالة

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**المستخلص:**

لقد ساهم تطور التكنولوجيا فى تحليل تفاعل كل مستخدم على الأجهزة الإلكترونية. حيث يترك السائحون «بصمة» رقمية في أغلب أنشطتهم في المدن التي يزورونها؛ يتم تحديد الموقع الجغرافي لكمية كبيرة من هذه البيانات. تمثل دراسة التفضيلات المكانية والزمانية للأفراد وأنماط الحركة عاملاً رئيسياً يجب أخذه في الاعتبار عند تصميم سياسات استخدام الأراضي الحضرية، حيث لا تزال المساهمات في دراسة السلوك المكاني للسياح الحضريين في المدن غير متوفرة. لذلك، تقدم الدراسة الحالية نظرة ثاقبة لسلوك المستخدم في البيئات الحضرية، مما يساهم فى تحديد وفحص المناطق التي يوجد بها تركيز كبير للأنشطة السياحية وتمكين تحديد المناطق غير النشطة داخل المنطقة الحضرية. الهدف الأساسي من هذا البحث هو تقديم منهجية لرصد مستوى نبض النشاط السياحي في المدن من خلال تحليل بيانات المحتوى الذي ينشئه المستخدم. تتجلى حداثة هذه الدراسة في عدة جوانب رئيسية: أولاً، تركز على التقاطعات بين أنشطة الطعام والتسوق ومشاهدة المعالم السياحية والاقامة في مدينة مختارة لدراسة الحالة؛ ثانيًا، يقدم طريقة جديدة لوصف مراكز النشاط السياحي الحضري وتحديد مجالات الاهتمام من وجهة نظر المستخدمين، وذلك باستخدام بيانات الشبكات الاجتماعية القائمة على الموقع من خلال استخدام تحليل المجموعات المكانية. ثالثًا، يتضمن الإطار المرجعي المقترح بيانات LBSN، لتكون بمثابة أداة تكميلية للتخطيط الحضري وعمليات صنع القرار التي تهدف إلى تحسين الديناميكيات الحضرية للمدينة. وبهذا المعنى، تم إجراء دراسة استكشافية باستخدام منهج دراسة الحالة في الإسكندرية، مصر من خلال استخدام برنامج نظم المعلومات الجغرافية-QGIS، إصدار بريزرن 3.32. لنتائج هذه الدراسة آثار كبيرة على مديري الوجهات السياحية والمخططين الحضريين والعلماء المهتمين بتحليل الديناميكيات الحضرية، لتوجيه تخطيط استخدام الأراضي الحضرية وصياغة استراتيجيات سياحية تتماشى مع التنشيط الحضري والتجديد لمعالجة الاختلالات في مختلف المجالات.

**الكلمات المفتاحية:** البصمة الرقمية السياحية، مراكز الأنشطة السياحية، الشبكات الاجتماعية المعتمدة على الموقع، بيانات التوسيم الجغرافي، البيانات المحددة للموقع، التحليل المكاني، التخطيط الحضري، الاسكندرية.