

# Data-Driven Visitor Tracking Analytical Insights and Recommendation System

Prof. Rutuja Khedkar, Abhijit Jawkar, Anushka Patil, Sharvayu Dhemse  
Dept. of Computer Engineering JSPM's Rajarshi Shahu College of Engineering Pune, India

**ABSTRACT:** - In an era of digital transformation, understanding visitor behavior in both digital and physical contexts is more important than ever to enhance the user experience and create business strategies. We introduce the Visitor Tracking, Analytics, and Recommendation System (VTARS)—an integrated framework for capturing, processing, and examining multi-modal visitor interaction data. VTARS uses state-of-the-art tracking methods to track individual visitor activity, interests, and actions across varying touchpoints. By combining data from multiple sources (for example, web analytics, location-based IoT services, and sensor networks), the system builds rich and comprehensive, yet dynamic, visitor profiles. The proposed framework utilizes machine learning algorithms and statistical models to analyze behavioral tendencies across browsing paths, purchase histories, and engagement frequencies. The output of the analytical process is presented in an interactive dashboard and visualization modules for stakeholders to view visitor interests and behavioral patterns in a common framework. Additionally, VTARS contains an adaptive recommendation engine that predicts user intent and recommends content, services or products contextual to the interaction. The system improves its predictive performance by learning over iterations, which allows user data-driven personalization and continuous improvements in user engagement and conversion performance.

**Keywords—** Visitor Behavior, Machine Learning, Recommendation System, Data Analytics

## 1.INTRODUCTION

In the current digital age, organizations are more interested in understanding visitor behavior to improve the user experience and decide strategically. To follow through with this initiative, organizations require the ability to systematically track visitors and analyze their activities and behaviors. To eliminate this problem, we have developed the Visitor Tracking, Analytics, and Recommendation System (VTARS), a platform that can track visitor activities in both online and physical environments and provide recommendations using actionable behavioral insights. VTARS uses various tracking methodologies to track individual users' actions and activities. VTARS builds individual visitor profiles by harnessing diverse data sources such as web analytics, location-based services, and Internet of Things (IoT) sensors. These visitor profiles summarize behavioral patterns, including content consumption, purchasing habits, and engagement frequency, to provide a comprehensive view of each visitor. After building a visitor profile, leveraging features from machine learning algorithms and statistical modeling, VTARS can identify new trends and recurring patterns of visitor behavior. VTARS has an analytics module, which produces interactive reports and visualizations for stakeholders and captures the visitor's demographics, interests, and engagement metrics in real-time reports. By using data about visitors, organizations can make informed decisions that ultimately improve the visitor experience, operational efficiency, and reallocate resources more effectively. In addition, VTARS features a smart recommendation engine that analyzes preferences and behavioral history of visitors in order to provide personalized suggestions based on context. Using both collaborative filtering and content filtering approaches, the system can effectively recommend products, services, or digital content that match the interests of individual users. Through real-time learning and adaptation, VTARS continually improves its recommendations over time, which facilitates higher user satisfaction, engagement, and conversion rates. In summary, VTARS is a comprehensive solution for organizations that want to use visitor analytics as a strategic advantage. By incorporating behavioral tracking, predictive analytics, and personalization the system improves customer engagement and loyalty, while improving the overall business performance as a increasingly competitive digital ecosystem.

## 2.LITERATURE SURVEY

An affordable system for indoor navigation and tracking has been created through Wi-Fi Received Signal Strength Indicator (RSSI) values to provide accurate localization of users. The system, called HandyMap, consists of a fingerprint mapping approach along with position estimation using the k-Nearest Neighbor (k-NN) algorithm, and determining the best navigation path using Dijkstra's algorithm. The framework was implemented on an Android mobile platform and connected to a Raspberry Pi 4B server for data processing and real-time tracking via a web-based application interface. Experimental results indicated the maximum localization was 78% accuracy under testing, with an average positioning error of 0.86 meters, and maximum error below 3 meters. The highest accuracy occurred using eight Wi-Fi routers for the test every three seconds allowing for indoor navigation while constantly tracking the subject's movement. (Nina, Arsharizka, et al.2023)

Using an Arduino Uno microcontroller and infrared (IR) sensors, a bi-directional visitor counting system was designed to count individuals reliably. Specifically the IR sensors formed the heart of the device by detecting both entry and exit, while the Arduino Uno acted as a motherboard for processing signals and data management. The visitor counting system communicated the visitor count in real time via an LCD module. The system was constructed in the Arduino Integrated Development Environment (IDE) and verified via Proteus simulation. For the hardware arrangement, the sensors were interfaced with a custom-designed printed circuit board (PCB) attached to an enclosure to keep the system stable and easy to handle. The experimental results indicate that the system effectively tracked how many individuals entered or exited in a controlled area to provide an accurate count of the occupancy in real time. The system provides a pragmatic approach toward crowd management and traffic monitoring in public or controlled environments, as it is simple, affordable, and reliable. (Vidushi, Nandini, et al.2023)

This study examined visitor mobility behaviors at the Fort Larned National Historic Site by employing a GPS-based Visitor Tracking (GVT) method. Participants were provided with GPS devices that allowed researchers to glean their spatial and temporal trajectories while visiting the site. Researchers processed the resulting data to create spatial heat maps indicating the most visited places on-site. The data showed a predominantly clockwise movement, with visitors beginning their experience at a key attraction and processed to the visitor center. The heat mapping also identified areas of low visitation, which can provide site managers insight into patterns or significant gaps in circulation patterns to better disperse or interpret visitors' flows around the site. Overall, the study illustrates that GVT offers researchers a unique method for understanding visitor flows, areas of congestion or low use, and suggestions for on-site interventions and strategies to improve visitors' engagement and experience. (Ryan, Ted, et al.2020)

The objective of this project was to create an intelligent visitor detection and monitoring system designed for small retail settings which includes the YOLOv4-tiny object detection model along with a Raspberry Pi and various other hardware components such as webcams and speakers. The model was trained for the purpose of human detection and had a mean Average Precision (mAP) of 89.21% indicating both accuracy and real-time performance. The proposed system is able to classify customers as either regular customers or potential shop lifters, based off of the behavioral pattern of the customers, and once a shop lifter was detected, using the Telegram messaging app, the store owner was immediately contacted alerting them of the potentially suspicious activity. This project, in addition to enhancing the overall security of a retail establishment improves customer engagement in an overall viewing/observing experience. Offering low-cost, small form-factor and an easy and efficient system to deploy makes the proposed solution a viable option for any small retail establishment, without the expense of an overpriced smart surveillance system. (Erlina and Fikri, 2023)

In another aspect of the study, sophisticated tracking methods, using Global Positioning System (GPS) technology, were deployed to gather spatial data of visitors' movements within a controlled theme park setting to understand visitor mobility and behavior. The tracking work, while initially narrow in its focus, was significant in demonstrating the merit of data collection to inform attraction management and optimization. The study also highlighted the need to consider issues of tracking visitors in less controlled environments like semi-open and outdoor attractions. It suggested that mobile-based tracking technologies could be used alongside, or in place of, GPS-based tracking systems to provide more detail and context for understanding visitors' behaviors. Issues stemming from privacy rights and device management requirements in outdoor settings were also discussed. Overall, this aspect of the study demonstrated how advanced visitor tracking technology can improve the operational effectiveness of attractions and destinations while also revealing possibilities for extending the approach to inform other tourism-related or urban contexts. (Russo, Clave, et al.2010)

The research team created and utilized an all-encompassing system for tracking individuals' locations using wireless communication with a specific focus on ZigBee technology, which supported real time visitor monitoring. The proposed system employed several localization approaches including time of arrival (ToA), received signal strength (RSS), angle of arrival (AoA), time difference of arrival (TDoA), and time of flight (ToF), to identify visitors' locations. Each visitor was linked to a separate transmitting device, which wirelessly communicated with reference nodes stationed within the environment approaching the designated paths pre-constructed. Visitors' positions and estimated times of arrival were frequently updated dynamically as they approached reference nodes, based on the RSS and delay in communication. To enhance the efficiency of data transmission between sensor nodes and the central computing system, a tree-based routing protocol which adheres to the ZigBee protocol was utilized, all while maintaining a stable network topology and data communication throughout the tracking process. Experimental results highlighted positive improvements with the localization accuracy, path estimation reliability, and real-time tracking reliability. The system improved overall visitor experience, accurate movement monitoring, and predicted next movement, especially in structured settings, such as university campuses, industrial life and settings. (Choi, Kim, et al.2013)

The researchers made use of multiple advanced analytical methods to achieve their research objectives. Data analyses were comprehensively conducted to examine existing data for underlying patterns and trends to support evidence-based decision-making. A primary focus of the study was on the construction of predictive models to forecast outcomes from what history had within the data. Simulation approaches were used to analyze various scenarios and how multiple variables would affect performance of the

system, while optimization methods further improved model performance and resource usage. To assess reliability, validation methods were used to investigate the accuracy and dependability of the results. The study found substantial evidence for improved predictive accuracy, leading to increased informed and timely decision-making. The findings also provided a big picture of what the data landscape contained, as well as potential next steps to inform practical and research directed improvements. Importantly, the model provided improvements around some of the scalability and adaptability to be potentially applicable outside this context. Overall, the project showcased the effective use and combination of multiple analytical approaches to inform robust, meaningful, and generalizable findings. (Ching, Prabuwno, et al.2009)

In a related study, the researchers undertook a comprehensive evaluation of a visitor management software system with a Grid View interface. The primary objective of this study was to evaluate the effects of the system on visitor management processes using both qualitative and quantitative data. The researchers collected primary data through interviews with key stakeholders, such as security officers, front desk staff, and visitors, as well as direct observation of operational practices. Secondary sources of data included organizational documents, visitor management policies, and historical visitor logs. The results revealed considerable improvements across several aspects of visitor management. The implementation of a system based on the Grid View interface resulted in increased operational efficiency, improved the user experience, and enhanced security processes. Specifically, the software improved check-in and check-out processes, decreased data entry error, and improved consistency and dependability of data. These results demonstrate the capacity of integrated software solutions to improve visitor management in organizational contexts. (Prateek and Prabhanjanpratap, 2023)

The authors constructed a complex system to detect suspicious acts through facial cues, including an emphasis on fear detection. This method implemented High-order Joint Derivative Local Binary Patterns (HJDLBP) which were computed along Local Binary Pattern (LBP) histograms and Support Vector Machine (SVM) classifiers to extract, and classify, based on expressions of emotion producing an accuracy rate near that of 69.3%. In addition to first-order features for emotion recognition, band-pass filtering was applied to analyze frequency components of the video signals through Eulerian and Lagrangian derived transformations to estimate heart rate in a potential physiological linking to fear response. The system was trained on the CK+ dataset and then evaluated in online video stream yielding a true recognition rate of 88.89% for fear detection. While real-time processing was difficult, the procedures ran more efficiently than prior methods for both facial expression detection as well as estimating physiological features. Also, implementation on a Raspberry Pi 3 showed processed estimates that adequate for low-cost portable use. This study as a whole provides an opportunity to process facial cues and physiological responses for determining suspicious behavior, and again highlights recognition and degree of emotions. (Ben Ayed, Elkosantini, et al.2019)

The research team created a multi-camera real-time people tracking system by using the YOLO object detection model combined with a Particle Swarm Optimization (PSO) algorithm to track each individual as accurately as possible. The system was intended to support continuity of tracking in the event an individual's trajectory took that individual across camera boundaries, with the hand-off occurring using an inter-camera hand-off protocol. To quantitatively assess tracking performance, the study introduced the Motion Smoothness metric that quantitatively assessed the trajectories' consistency of motion. An experimental evaluation of the system was completed with two individuals and three cameras, which showed strong tracking performance with 96.00% of positional errors remaining below 30px and only 0.15% of frames having notable differences. The results show that the system can support accurate and smooth multi-camera tracking in real-time. (Yi-Chang, Ching-Han Chen, et al.2021)

### 3. METHODOLOGY

The application utilizes a scalable technical framework consisting of backend data storage, APIs, and system architectures that enable continuous tracking of GPS-enabled visitors to engage and interact with visitors. A visitor accesses the web application and enters basic data such as name, location/area of park, age and permission for location tracking. The virtual parameter setting occurs through geofencing technological capabilities to track visitor movement and engagement in the park. The data collected is conveyed to a centralized processing and storage system, enabling cleaning, data processing, and noise reduction by technologies such as Apache Flink, Apache Spark, and PyTorch. Analysis of behavior occurs through visualization and analytical platforms including Tableau, Power BI, and Apache Spark; these insights show visitors' routes taken, while also sketching the preferences and engagement type experienced (for example, areas visited and duration of respective session). Reporting on the [engagement] uses tools such as Mapbox, QGIS, and Qlik Sense to summarize dashboards and maps and provides actionable intelligence to improve visitor experience and appropriate park management.



Figure 1. Proposed Method Architecture

### 3.1 Analytical System

#### 3.1.1 Data Collection:

The Visitor Tracking, Analytics, and Recommendation System (VTARS) begins by synthesizing data from multiple sources for a more holistic picture of visitor engagement. Web analytics represent one of the key data sources and track page views, click through rates, session duration, and navigation. Similarly, location-based services track movement in physical space, and can measure frequency of visits by tracking foot traffic, dwell times, and movement. VTAR integrates existing IoT-augmented tracking systems which allow tracking of visitors' interactions with physical objects in environments, providing a transition from digital to physical tracking of the visitor journey. For geospatial tracking, the system utilizes Google Maps API, Leaflet.js, and OpenStreetMap technologies.

#### 3.1.2 Data Analysis:

VTARS emphasizes providing actionable business insights through large-scale visitor data. Descriptive analytics allows researchers to provide summaries of behavior in the historical data, and specific metrics to support visitor engagement insights, such as average duration of visit, visitor page metrics (most visited, least visited), and movement metrics (common movement path). Predictive analytics can be used to develop machine learning algorithms to predict future behaviors and trends in visitor engagement, allowing organizations to better anticipate visitor needs and provide proactive strategies in accommodating visitor expectations. Behavioral segmentation enables the development of typologies that account for visitors that share similar characteristics with respect to visitor engagement experience, thereby having an identify typologies the to create and employ a targeted marketing plan and continue to engage with those that share common traits or design custom experiences if possible. A few of the analytical models utilized within VTARS include Logistic Regression, Decision Trees, and Random Forests analytical models which provide robust and interpretable insights into visitor behavior dynamics.

#### 3.1.3 Pattern Recognition:

The VTARS platform has an edge-based pattern recognition module for visitor behavior analysis and data-informed decision making. This module is designed to identify consistent patterns within product categories or content preferences, so businesses can take proactive action on emerging opportunities. Coupled in the trend analysis, VTARS also has the ability to recognize anomalous or "unexpected" visitor behavior that strays from established norms, which may reveal problems with customer experience or shifts in demand. Places of high density visitation are captured in D3.js and heatmap.js, providing a visual representation of visitor engagement and interaction patterns in space.

#### 3.1.4 Visualization and Reporting:

VTARS provides extensive visualization and reporting to turn complex behavior data into actionable insights. The systems allows for real time dashboards and customizable reports based on business-centered needs of highlighting key findings and tactical recommendations. Graphical and visual tools like heatmaps and flow charts have been developed for visual representations of visitor

movement and interaction patterns both online and in the physical space, that allow for stakeholders to interpret complex datasets, expose potentially important trends, and make time sensitive and informed decisions.

### 3.1.5 Safeguarding Security and Privacy:

With the growing importance of data privacy, VTARS emphasized security and privacy compliance. We will protect visitor data against unauthorized access and data breaches using security measures such as encryption, secure data storage, and access control. We additionally align with major data protection regulations and standards, such as the General Data Protection Regulation (GDPR) and California Consumer Privacy Act (CCPA) to ensure responsible use of personal data. The system will use TLS/SSL protocols to ensure secure communication so that organizations can be confident that visitor data is being processed in a secure, compliant, and privacy-conscious manner.

## 3.2 Recommendation System

### 3.2.1 The Recommendation Engine:

A key aspect of VTARS is the recommendation engine, which offers personalized content, products, or services to unique visitors. It uses two major algorithms: collaborative filtering and content-based filtering. The recommendation engine creates recommendations based on analysis of the behaviors of users who are similar to a unique user, while the content-based filtering method creates recommendations based on the attributes of the content that the user has engaged with previously. To improve the relevance and accuracy of recommendations, VTARS will utilize a hybrid method of incorporating both collaborative filtering and content-based filtering algorithms. The recommendation engine will provide recommendations for additional items that users can engage, that are closely aligned with their preferences and interests.

### 3.2.2 Data Inputs for Recommendations:

The recommendations engine service utilizes numerous data inputs to create personalized recommendations. Detailed user profiles, developed through the analysis of visitor tracking and behaviors, share details of the users' past interactions, preferences, and cohort characteristics. Contextual information (e.g., time of day, users' location, and device type) is integrated to improve recommendations further. A visitor's interests can change based on their location (e.g., in- store versus online) or based on the device they are using (e.g., desktop versus mobile), and the recommendation engine dynamically adapts to those contextual characteristics. This multi-dimensional approach allows VTARS to produce timely, relevant, context-sensitive recommendations to maximize visitor engagement and satisfaction.

Recommendation System			
Accuracy	88%		Percentage of correct recommendations.
Precision	91%		Proportion of relevant recommendations among all recommendations.
Clustering Accuracy	93%		Effectiveness in segmenting visitors into meaningful groups.

Table 1: Recommendation System

### 3.2.3 Recommendations Filtering:

VTARS has two main recommendation filtering techniques: collaborative filtering and content-based filtering. Collaborative filtering creates recommendations by finding patterns in individuals wherever they display behavioral similarities and preferences, allowing the system to recommend items that similar users engaged with or purchased. Content-based filtering creates recommendations by analyzing how similar the item is to other items already interacted with by the user based on item attributes, like category or feature. In VTARS, collaborative filtering is based on matrix factorization and content-based filtering uses item property analysis as its means of producing very targeted recommendations.

### 3.2.4 Real-time Processing:

VTARS keeps recommendations current and relevant through real-time processing. Once a user engages with an object, that engagement gets processed immediately, and the recommendation system can update recommendations based on activity at that very moment. This keeps users receiving timely and relevant engagement and recommendations, which enhances the overall experience and guarantees repeated engagement with the system. Additionally, VTARS is capable of scaling, where the recommendation engine can handle large amounts of data and large numbers of users without any degradation in performance, making VTARS applicable in businesses of varying sizes.

### **3.2.5 Incorporating User Feedback:**

A distinctive feature of VTARS is its ability to incorporate user feedback to improve the precision and appropriateness of recommendations. Feedback is gathered through two forms of feedback – explicit feedback in the form of user-supplied ratings and reviews, and implicit feedback as a result of user interactions: frequency of clicks, time spent on pages, and engagement. The incoming feedback is consistently scrutinized and assessed in regards to refining the recommendation models, enabling VTARS's the capacity to adapt over time to an evolving user preference. By utilizing both explicit and implicit signals in the feedback mechanism, the system incrementally personalizes recommendations, resulting in an increase in accuracy, while overall user satisfaction improves over time.

## **4.USER EXPERIENCE**

### **4.1 Personalized User Journeys:**

VTARS facilitates personalized user journeys by customizing engagement based on visitor information. The system records a user's actions and behavior across a variety of touchpoint locations, both online and offline, and uses that data to recommend content, products, and services that fit visitor preferences. Each user experiences a tailored interaction based on historical interaction history--an experience that enhances satisfaction and repeat engagement. The personalization of the user journey is extended across touchpoint locations, including websites, mobile apps, and in-store locations--providing the same personalized experience no matter the user's touchpoint location.

### **4.2 Real-time Engagement:**

Real-time engagement also enhances user experience with VTARS. The system continuously and actively monitors user engagement and engages in real time based on behavior. For example, if a visitor engages with one product category, VTARS can immediately provide other product recommendations or promotions to the visitor based on their interests. The continuous, real-time engagement is designed for maximum interactivity and personalization. Real-time interaction improves user satisfaction, while supporting higher conversion rates by meeting visitors' perceived needs in a timely manner.

### **4.3 Support and Guidance:**

Proactively enhancing the user experience, VTARS offers support and guidance throughout the visitor journey. In the example of a user who appears to stay on an FAQ page for too long, the system would infer there is a need for assistance, and provide a live chat, tips, or instructions on what to do next. Supporting users as they encounter barriers, or experience any frustrations, would enhance onboarding/resolving user need by anticipating when users need assistance, reducing frustration, handling any service need in a timely manner, and offering the appropriate support, VTARS strives to improve upon enhancing user experience and engagement.

### **4.4 Feedback and Continuous Improvement through Systematic Feedback Integration:**

VTARS features continuous improvement through systematic feedback integration. Feedback from users will be intentional (explicit) through surveys and ratings, or receive feedback from implicit signals, such as engagement metrics and user behavioral information, to identify opportunities of improvement and adjust accordingly to improve user experience. Specifically, through taking these feedback loops into account, VTARS has a continuous process of enhancing its interface, interactions and recommendations to provide seamless, efficient and adaptive user experiences in both digital and physical interactions and experiences.

## **5.RESULTS**

### **5.1 Location**

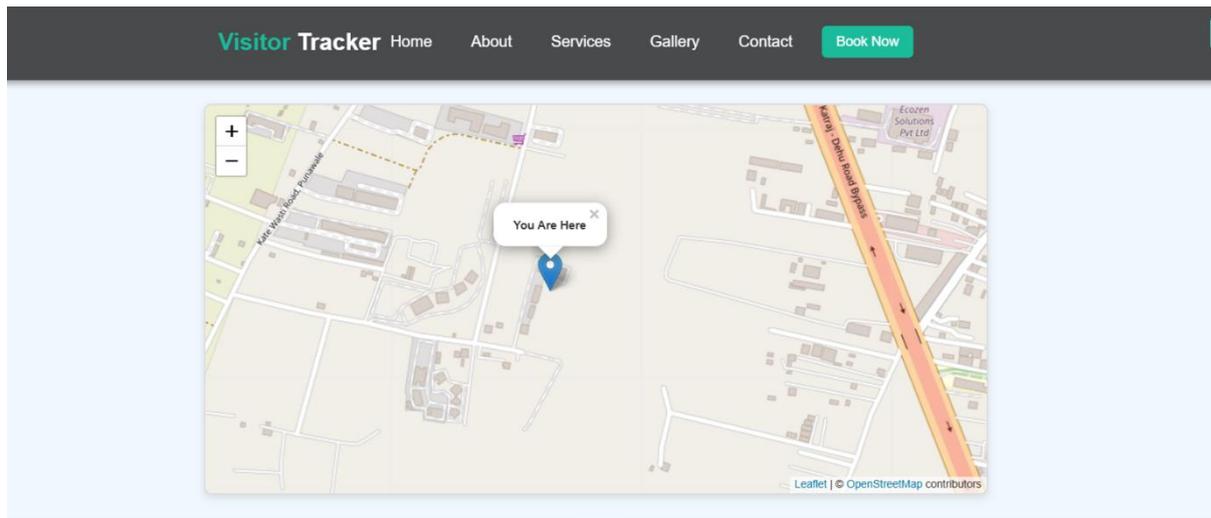


Figure 2. Location Interface

The successful deployment of the real-time geolocation tracking system, now referred to as VisitorTracker, resulted in a working web interface capable of accurately mapping the position of a monitored device. Outputs from the system demonstrated faithful resolution of streamed GPS coordinate data, which were shown as a unique blue marker on the interactive map with a “You Are Here” tooltip, thus confirming the integrity of the data pipeline from obtaining sensor data to visualization. As a digital leaflet-based map with OpenStreetMap data, the interface delivered high-resolution, context-specific view with surrounding streets and buildings while providing standard interactive zoom controls to verify the accuracy of location at various scale levels. The outcomes confirm that the VisitorTracker system is sufficiently effective for the first aspect of real-time reliable geolocation tracking in a detailed geography.

## 5.2 Visitor Behavior

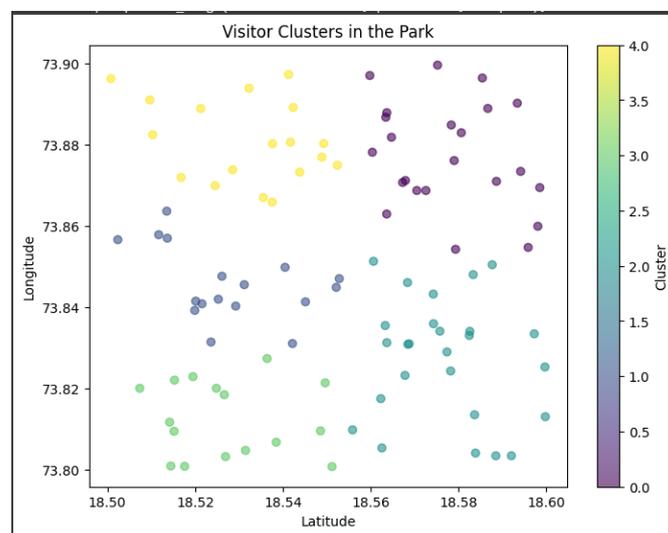


Figure 4. Visitor Behaviour

Using a density-based clustering algorithm applied to clustered visitor geolocation data, the movement of visitors within the park was clustered in four distinct spatial clusters (0-3, as shown in the accompanying color scale). The clusters demonstrated uneven spatial distributions that emphasized visitor activity levels in concentrated locations: Cluster 0 (purple) was mainly confined to the northern area (higher longitude) while the majority of Cluster 3 (green) was found towards the southwestern corner (lower longitude and lower latitude). These represent substantial and predictable spatial variability in visitor choice and behavior, and we have demonstrated that visitors move in non-random ways and in distinct areas of the park. In addition to defining spaces in which movements occur, this segmentation of behavior also provides key information into VTARS, paving the way for recommendations such as suggesting attractions of high visitor interest (e.g. the Ferris Wheel) or calculating shortest routes between attractions, and thus provide recommendations for managing visitor flow and overall enhance visitor experience.

### 5.3 Recommendation System

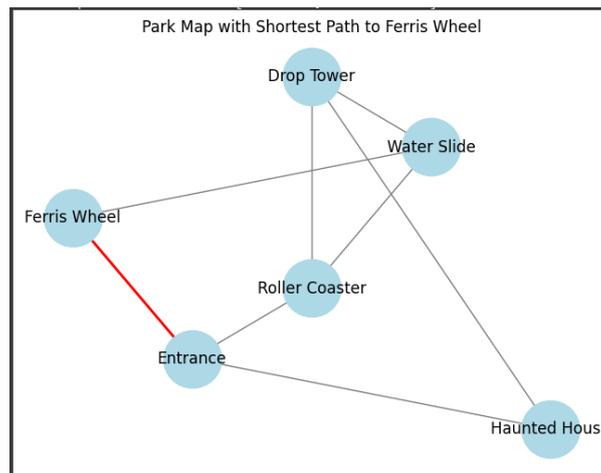


Figure 5. Recommendation System

The third part, Recommendation system combines a shortest path algorithm to offer directional recommendations based on visitor segmentation and anticipated attraction wait times. In the context of the park model, attractions are represented as nodes (e.g., Entrance, Ferris Wheel, Drop Tower) and physical walkways are represented as edges (grey lines). Once a recommended attraction is identified for a specific time (e.g., Ferris Wheel at 3 PM), the system will calculate the optimal route from the location of the visitor (e.g., Entrance) to the recommended attraction. The calculated shortest path will be highlighted visually (red edge) on the map of the park, confirming the algorithm is identifying a potential route (['Entrance', 'Ferris Wheel']). This demonstrates the system's ability to transfer analytical discovery from visitor behavior to immediate real-time and optimal direction to improve visitor experience and operational efficiency.

## 6. CONCLUSION

The VTARS analytical system incorporates real-time geolocation tracking, behavioral segmentation, and optimized navigation guidance to improve visitors' experiences at theme parks. The VisitorTracker component provides GPS coordinates in real-time and allows for their visualization on interactive maps built with Leaflet and OpenStreetMap, confirming the validity of the data pipeline, from data acquisition by the sensor to the visualization of data in the user interface. A density-based clustering algorithm, applied to aggregated visitor behavior data, identified movement patterns segmented into four unique spatial clusters which captured locations characterized by predictable clustering coinages that enable actionable insights related to crowd management and attraction recommendations. Based on patterns identified by the clustering algorithms the systems shortest path optimized movement using visitor location and recommended attractions, highlighting paths of least resistance in real-time enhancing visitor experience, and reducing congestion. These capabilities collectively allow VTARS to finely measure visitor movements, identify behavioral patterns, and provide visitors with data-informed recommendations that support satisfaction, efficiency of operations, and overall engagement with a theme park, showcasing the capability of the system to convert analytical visitor behavior data into personalized, actionable, and practical solutions.

## 7. REFERENCES

- [1] Nina, Siti Aminah, Arsharizka, Syhadati Ichwanda, Daryanda, Dwiammardi Djamal, Yohanes, Baptista Wijaya Budiharto, Maman, Budiman (2023) A Low-Cost Indoor Navigation and Tracking System
- [2] Singh, Vidushi and Rathi, Nandini and Choudhary, Khushi and Gupta, Pragya and Mehendale, Ninad, "Design and Development of Bidirectional Visitor Counter using Arduino Uno Micro-Controller and IR Sensors" (May 10, 2023).
- [3] Ryan L. Sharp, Ted T. Cable, Aubrey Burns "The Application of GPS Visitor Tracking Implications for Interpretation at Heritage Sites", journal of interpretation research (0975 – 8887) Volume 24 – No. 1, September 2020
- [4] Erlina, T., & Fikri, M. (2023). "YOLO Algorithm-based Visitor Detection System for Small Retail Stores using Single Board Computer." *Journal of Applied Engineering and Technological Science (JAETS)*, 4(2), 908–920
- [5] Russo, A.P., Clave, S.A., Shoval, N. (2010). "Advanced Visitor Tracking Analysis in Practice: Explorations in the PortAventura Theme Park and Insights for a Future Research Agenda." In: Gretzel, U., Law, R., Fuchs, M. (eds) Information and Communication Technologies in Tourism 2010. Springer, Vienna. DOI.org (Crossref),
- [6] S. -H. Choi, S. -Y. Kim and Y. -C. Ra, "A Study on Visitors Tracking Method Using Wireless Communication," 2013 International Conference on Information Science and Applications (ICISA), Pattaya, Thailand, 2013,
- [7] Y. K. Ching, A. S. Prabuwo and R. Sulaiman, "Visitor face tracking system using OpenCV library," 2009 IEEE Student Conference on Research and Development (SCORED), Serdang, Malaysia, 2009

- [8] Prateek, K. and Prabhanjanpratap, S. K. "Company Visitor Management Software", 2023. International Research Journal of Modernization in Engineering Technology and Science
- [9] M. Ben Ayed, S. Elkosantini, S. A. Alshaya and M. Abid, "Suspicious Behavior Recognition Based on Face Features," in IEEE Access, vol. 7, pp. 149952-149958, 2019.
- [10] Wu, Yi-Chang, Ching-Han Chen, Yao-Te Chiu, and Pi-Wei Chen. 2021. "Cooperative People Tracking by Distributed Cameras Network" *Electronics* 10, no. 15: 1780.
- [11] R. G. Khedkar, S. R. Tandle "Rating Prediction based on Social Sentiment from Textual Reviews", International Journal of Computer Applications (0975 – 8887) Volume 178 – No. 26, June 2019
- [12] Dr. Nilesh B. Korade , Dr. Mahendra B. Salunke , Dr. Amol A. Bhosle , Dr. Prashant B. Kumbharkar , Gayatri G. Asalkar , Rutuja G. Khedkar "Strengthening Sentence Similarity Identification Through OpenAI Embeddings and Deep Learning" (IJACSA) International Journal of Advanced Computer Science and Applications, Vol. 15, No. 4, 2024
- [13] R. G. Khedkar, S. R. Tandle "Rating Prediction based on Social Sentiment from Textual
- [14] Dr. Nilesh B. Korade, Dr. Mahendra B. Salunke, Gayatri G. Asalkar, Rutuja G. Khedkar, Ashwini U. Bhosale, Dhanashri M. Joshi, Amol C. Jadhav "Exploring NLP Techniques for Duplicate Question Detection to Maximizing Responses on Q&A Websites" International Journal of Intelligent Systems and Applications in Engineering IJISAE, 2024
- [15] A. Joshi, P.G., "Algorithm for Safety Decisions in Social Media Feeds Using Personification Patterns", JAIT, Vol. 14, No. 1, 2023
- [16] V. Kumbhar, U. Maurya, et.al, "Crevice Identification: A Survey on Surface Monitoring," 2023 IEEE International Conference on Contemporary Computing and Communications (InC4), Bangalore, India, 2023
- [17] Rudenko et al., "Human motion trajectory prediction: a survey — comprehensive taxonomy and methods for trajectory forecasting", 2020
- [18] Alahi et al., Social LSTM: "Human Trajectory Prediction in Crowded Spaces — foundational RNN/LSTM model that models social interactions between pedestrians", 2016
- [19] Gupta et al., Social GAN: "Socially Acceptable Trajectories with Generative Adversarial Networks", 2018
- [20] N. Wojke, A. Bewley, D. Paulus, "Simple Online and Realtime Tracking with a Deep Association Metric (DeepSORT)", 2017
- [21] Y. Zhang et al., "Single-Image Crowd Counting via Multi-Column Convolutional Neural Network (MCNN)", 2016
- [22] J. Xiao et al., "A Survey on Wireless Indoor Localization from the Device Perspective", 2016
- [23] P. Roy et al., "A survey on ubiquitous WiFi-based indoor localization", 2020
- [24] L. Zheng et al., "Person Re-identification: Past, Present and Future", 2016
- [25] Hermans, L. Beyrer, B. Leibe, "In Defense of the Triplet Loss for Person Re-Identification", 2017