



Mining User Mobility Insights from Public Wi-Fi Data Using Association Rules in Urban Riverfront Areas

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ABSTRACT

Understanding user mobility patterns is essential for effective urban planning and resource management. This study employs Association Rule Mining to analyze public Wi-Fi data collected from 11 access points along the Mekong River in Sri Chiang Mai, Thailand, from May 2022 to December 2023. By examining co-occurring movement patterns in over 73.7 million connection records, the research uncovers key insights into human behavior in the area. The findings highlight the area in front of the Fresh Market as a central destination, with confidence values exceeding 0.99 for related movement rules. The results reveal pronounced temporal variations in movement patterns, with transitions from commercial areas in the mornings to leisure spaces in the afternoons and evenings. Weekday patterns differ notably from weekend behaviors, reflecting how time influences urban space utilization. These insights provide urban planners and policymakers with data-driven evidence to optimize infrastructure development, enhance public spaces, and improve resource allocation. Although this study is limited to Wi-Fi data, it provides significant contributions to the development of smart cities that are more responsive and sustainable, paving the way for improved urban living experiences and more efficient resource management. Future work could integrate multiple data sources to enable more comprehensive mobility analysis and advance sustainable urban development goals.

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1. INTRODUCTION

User mobility is a critical factor in understanding urban dynamics, providing valuable insights into human behavior, land use, and urban planning [1, 2, 3, 4]. Traditional methods for studying mobility primarily rely on GPS sensors and mobile phone data, as demonstrated by several recent studies [5, 6, 7,

8]. However, these approaches are subject to several limitations. Privacy concerns are a major issue when dealing with personal location data [9, 11]. The implementation and data processing costs can be prohibitively high [10], and potential biases in data collection can affect the reliability of results [12].

For example, Ball and Sağbaş [5] used mobile phone data for transportation mode diagnosis, while

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Lin and Chan [6] visualized population mobility using mobile phone data, showcasing the potential of these methods. However, these approaches are not without challenges, as highlighted by the privacy-preserving frameworks proposed by Liu *et al.* [9] and Savi *et al.* [11]. Additionally, Yang *et al.* [10] pointed out the need for efficient data aggregation methods to address cost and privacy constraints.

To address these challenges, modern detection technologies such as Wi-Fi have become increasingly popular for studying user mobility across expansive areas [13, 14, 15]. The growing ubiquity of public Wi-Fi technology has emerged as an alternative data source for studying user mobility [16, 17, 18]. Public Wi-Fi networks can capture signals from Wi-Fi-enabled devices, enabling tracking of their movements as they connect to different access points [19, 20]. This approach leverages existing infrastructure, making it a more cost-effective and scalable solution for understanding user mobility patterns [21, 22].

Association rule mining (ARM) is a data mining technique that can be applied to Wi-Fi data to discover co-occurring movement patterns. By identifying frequent patterns of movement between different locations, researchers and urban planners can gain a deeper understanding of how people interact with and navigate through urban environments [22, 23, 24].

Sri Chiang Mai, with its unique blend of historical significance and emerging urban challenges, offers an ideal context for investigating contemporary mobility dynamics. The city's ongoing effort to balance cultural heritage preservation with increasing demands from urban growth and tourism makes it a compelling case for data-driven mobility research. Leveraging public Wi-Fi access-point data provides a non-invasive and cost-effective means of capturing real-world movement behaviors of both residents and visitors, addressing a longstanding challenge in tourism-intensive urban environments. Moreover, the application of ARM enables the discovery of complex, non-linear mobility relationships that traditional techniques may overlook, thereby enriching our understanding of spatial and temporal movement patterns within the city. Beyond advancing local insights, this study contributes to the broader discourse on smart city development, offering analytical approaches and empirical findings that can inform sustainable urban planning and policy decisions in similar cities worldwide.

The main contributions of this study are as follows:

1. We provide a spatio-temporal analysis of user mobility along the Mekong Riverfront in Sri Chiang Mai using public Wi-Fi access-point data, revealing predominant movement flows and central activity hubs.
2. We identify temporal variations in mobility patterns across times of day and days of the week, offering deeper insights into dynamic urban movement

behaviors.

3. We evaluate the applicability of ARM for urban mobility analysis and derive data-driven recommendations to support urban planning and resource allocation.

4. We provide a rigorous validation of the time-aware approach by comparing it with a time-agnostic model. This comparison demonstrates the dilution effect in large-scale datasets, suggests that temporal segmentation is essential for uncovering high-confidence mobility patterns that would otherwise be statistically obscured.

2. LITERATURE REVIEW

The study of urban mobility encompasses a range of scientific principles, including data management and analysis. To enhance the understanding of movement patterns in urban areas, identifying key locations and their utilization by residents and visitors is crucial. This study aims to achieve this objective by leveraging public Wi-Fi data. Therefore, this section highlights several essential elements of this approach, including the use of technology to study user mobility, ARM for mobility analysis, and user mobility management and sustainability.

2.1 Using Technology to Study User Mobility

Survey-based methods for studying urban behavior often suffer from recall bias and participant burden. Technology-driven approaches offer more accurate and privacy-aware alternatives. For example, GPS-based tracking in Finland introduced a platform that processes GNSS data before publication, enabling citizens to share anonymized activity data for research [25]. Indoor tracking using BLE beacons and the RNSI method improves location prediction accuracy over RSSI, though structural interference remains a challenge [26]. Social media data, such as Weibo check-ins, has been used to infer home and work locations and identify activity-specific sites in Beijing, addressing sample bias [27].

Wi-Fi-based mobility tracking provides passive, cost-effective sensing by capturing probe requests from mobile devices, enabling comprehensive spatial and temporal analysis [28]. Public Wi-Fi networks further enhance scalability, as demonstrated in Palma, Spain, where AI techniques modeled urban mobility using device frequency, transport mode estimation, and route identification [20]. This study leverages Sri Chiang Mai's existing public Wi-Fi infrastructure along the Mekong River, aligning with smart city initiatives that utilize existing resources for sustainable urban planning [29].

2.2 Association Rule Mining in Mobility Analysis

Decoding complex urban movement patterns is a key challenge in mobility research [30]. Traditional trajectory-based methods, such as sequential pattern mining, often overlook associations between locations and times [31]. ARM addresses this gap by identifying co-occurrence patterns within large datasets, revealing relationships beyond strict sequences [22, 23, 24, 32]. Unlike sequential mining, ARM focuses on frequent co-visits, offering insights into spatial and temporal dynamics of urban space use.

ARM, widely applied in retail for uncovering product associations, commonly uses the FP-Growth algorithm for efficient pattern extraction [33, 34]. Applied to public Wi-Fi data, ARM enables detection of frequent routes and co-occurring site visits, supporting mobility analysis [22]. For example, a study in Hokkaido, Japan, used Wi-Fi tracking and ARM to analyze tourist flows, informing infrastructure and experience design [24]. Integrating ARM into urban mobility research provides a flexible approach for identifying high-traffic areas and underutilized spaces, advancing sustainable urban planning [35]. To further distinguish the novelty of this research, Table 1 provides a comparative summary with existing Wi-Fi-based mobility studies. Unlike prior works that often focus on smaller tourist datasets, this study leverages a massive 73.7 million record dataset to capture granular mobility dynamics in a riverside community through a highly segmented temporal lens.

Table 1: Comparison with Existing Wi-Fi Mobility.

Study	Methodology	Dataset Scale	Context	Temporal Analysis
Versichele et al. [32]	ARM (Bluetooth)	Small scale	Tourism (ghent)	Yes
Arreeras et al. [24]	ARM (Wi-Fi)	1.8 M records	Tourism (Hokkaido)	Yes
Salas et al. [22]	AI / ARM (Wi-Fi)	N/A	Smart City (Palma)	Limited
This Study	Time-aware ARM	73.7 M records	River front Community	High (Segmented)

2.3 User Mobility Management and Sustainability

Managing mobility is critical for smart city sustainability. Prior studies introduced PMM, achieving >85% path accuracy and processing 14,177 GPS pairs per second, and AFNextPOI, which distinguishes routine behaviors using Isolation Forest and DBSCAN, outperforming state-of-the-art models [40, 41]. Public Wi-Fi offers a cost-effective, scalable al-

ternative for real-time mobility tracking without additional infrastructure [20].

Wi-Fi data identifies high-traffic areas, peak times, and movement patterns. In Palma, Mallorca, it supported transport mode estimation and route identification for urban planning [22]. ARM further enhances analysis by uncovering frequent routes and temporal dynamics, as demonstrated in Hokkaido, Japan, for sustainable tourism planning [24].

Sustainable mobility reduces environmental impact and improves quality of life through interventions such as traffic control, shaded public spaces, seating, and improved lighting [36]. Integrating Wi-Fi data with advanced mining techniques enables accurate mobility models, supporting responsive, sustainable urban environments [37].

3. MATERIALS AND METHODS

3.1 Data Sources

3.1.1 Case Study: Public Wi-Fi Infrastructure in Sri Chiang Mai

In 2022, the Sri Chiang Mai Municipality launched a pilot initiative known as the “Sri Chiang Mai Smart City Free Wi-Fi,” in partnership with the National Telecom Public Company Limited (NTPLC), a leading telecommunications company in Thailand. This initiative involves the deployment of a public Wi-Fi network consisting of multiple access points (APs) that provide wireless connectivity to mobile devices. These APs are strategically placed at 11 locations along the Mekong River, which are prominent tourist spots in the city. Figure 1 illustrates the various AP installation sites, highlighting the active APs along the Mekong River.

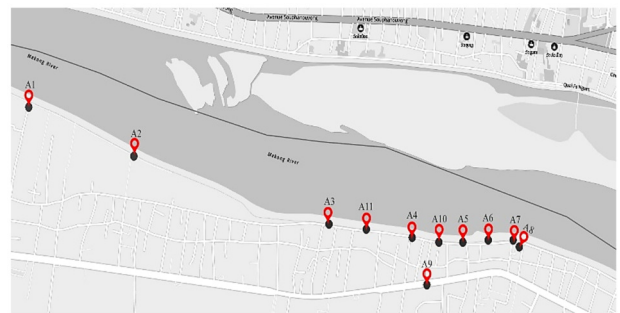


Fig.1: Study Area and AP Distribution.

In Fig. 1, we conducted the field experiment at various attraction nodes along the route network, including agricultural areas, community activity buildings, event spaces, parks, religious places, community markets, exercise areas, and city landmarks. Additionally, it included popular attractions such as city landmarks, parks, and event plazas, details as shown in Table 2.

To ensure a comprehensive understanding of the dataset prior to applying Association Rule Mining

Table 2: AP Installation and Observation Locations.

ID	Genre	Location
A1	AA	Klong-soi-1 Bridge
A2	CAB	Village Fund Building
A3	RS	In front of Chang Phueak Temple
A4	RS	In front of Klang Temple
A5	CL,PK	Sri Chiang Mai
A6	CL, ES	Naga Courtyard
A7	RS, ES	In front of Had Pathum Temple
A8	ES	Boeng Wiang Courtyard
A9	CM	In front of Fresh Market
A10	EA	Soi-19
A11	EA	Soi-16

Agricultural Areas (AA), Community Activity Buildings (CAB), Event Space (ES), Parks (PK), Religious Places (RP), City Landmarks (CL), Community Market (CM), Exercise Area (EA)

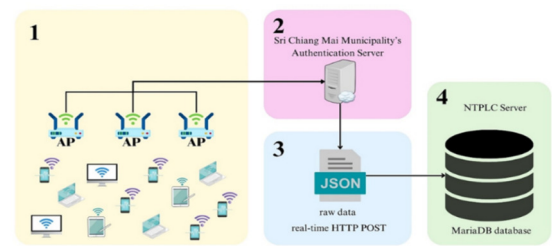
(ARM), an exploratory data analysis (EDA) was conducted to identify underlying patterns, detect anomalies, and validate data quality. The dataset comprises over 73.7 million Wi-Fi connection records collected between May 22, 2022, and December 31, 2023, from access points deployed along the Mekong River in Sri Chiang Mai. Each record includes a timestamp, an anonymized device identifier, and an access point location; after preprocessing and deduplication, approximately 71.5 million valid records were retained for analysis. Notably, on December 31, 2022, two access point locations were relocated—from Klong-soi-1 Bridge to Soi-19 and from the Village Fund Building to Soi-16—to optimize network coverage. The study area represents a prominent riverfront zone that attracts both residents and tourists, resulting in consistently high levels of user activity. From a temporal perspective, the data exhibit clear daily and weekly patterns, with peak activity observed during morning (06:00–11:59) and evening (17:00–23:59) periods, corresponding to market and leisure activities, respectively, while weekends show greater variability and increased evening activity compared to weekdays. Spatially, the distribution of connections is highly uneven across access points, with the Fresh Market location (A9) consistently recording the highest number of connections, indicating its role as a primary activity hub, whereas peripheral locations such as Soi-16 (A11) and Soi-19 (A10) exhibit relatively lower interaction levels. In terms of user behavior, session-based analysis indicates that most devices connect to multiple access points within short time intervals, reflecting localized movement patterns rather than long-distance transitions, while frequent transitions between specific location pairs (e.g., A5–A6 and A7–A8) further highlight recurring mobility loops within the study area. In addition, descriptive statistics of device usage reveal that the distribution of connection

frequency per device is highly skewed, with a relatively low mean and a high standard deviation, indicating that most devices connect only a few times, whereas a small subset exhibits frequent connections, suggesting the coexistence of transient users and regular visitors. Overall, the EDA confirms that the dataset demonstrates strong temporal regularity, spatial concentration, heterogeneous usage behavior, and repeatable movement patterns, thereby justifying the application of ARM as an appropriate method for discovering co-occurring mobility behaviors in large-scale transactional datasets.

3.1.2 Existing Dataset Utilization

This research utilizes the existing Wi-Fi connection dataset collected from the Sri Chiang Mai Smart City Free Wi-Fi infrastructure as detailed in [38]. The dataset was originally collected using Wi-Fi access points functioning as sensors to capture data from Wi-Fi-enabled devices, such as mobile phones, throughout the study area.

Fig. 2 illustrates the data flow and infrastructure setup for the public Wi-Fi network system implemented by Sri Chiang Mai Municipality in collaboration with NTPLC. This diagram shows how the original data were collected and processed, providing context for understanding the dataset used in the current analysis. The system architecture comprised multiple Wi-Fi APs connected to mobile devices via wireless signals, with each AP capturing data from devices within its coverage area. The authentication server, part of the Sri Chiang Mai Municipality's infrastructure, received and processed this data before forwarding it to NTPLC's MariaDB database in JSON format.

**Fig.2:** Sri Chiang Mai Public Wi-Fi Architecture and Data Flow.

The dataset comprises over 73.7 million connection records (May 2022–December 2023), each including a timestamp, an anonymized device ID, and a location ID. Its structure, shown in Table 3, enables the analysis of tourist movement patterns using ARM without additional data collection.

Table 3: Sample of data converted into a simplified format for further analysis and utilization.

timestamp	device id	site id
2022-06-11 06:59:02	35	9
2022-06-11 07:25:02	21	7
2022-06-11 07:31:02	495	8
2022-06-11 08:03:04	3387	8
2022-06-11 08:07:04	5043	4
2022-06-11 09:56:03	588	7
2022-06-11 10:00:04	6433	3

The system ensures secure data handling and seamless integration of collection, authentication, transmission, and storage within the public Wi-Fi network, supported by Sri Chiang Mai Municipality and NTPLC. Device communication records are stored in a MariaDB database with three fields, as summarized in Table 4.

Table 4: The fields and descriptions for device communications are in the MariaDB database.

Fields	Descriptions
timestamp	A timestamp is the recorded date and time when the device is detected.
deviceid	The MAC address is modified, encrypted with SHA-256, and tokenized to generate an ID that cannot be reverse-engineered to the original address.
siteid	Access Point Installation Sites where the MAC address is connected.

3.2 Preprocessing Data

To conduct the ARM analysis using Python, it was necessary to prepare the dataset. This research focused on identifying transaction patterns from the APs request dataset, taking into account only continuous transactions over time as valid transaction data, as illustrated in Table 3. An example of transaction records and a continuous pattern suitable for ARM is illustrated in Table 3. The dataset was selected based on the identification of identical MAC addresses, which serves as deviceid, and the identification of different locations represented by siteid in the last column, along with the date and time. Since the MAC address serves as a proxy identifier for a device visiting the location and remains constant, capturing the same MAC address at different locations with sensors indicates the movement of individuals

from one place to another.

3.2.1 Data Cleaning

Data cleaning was performed in three steps:

1. Access Point Integration: To minimize signal interference from buildings, walls, or trees, high-performance APs were installed in unobstructed locations (e.g., poles) to ensure stable data transmission and reduce loss.

2. Filtering Long-Term Connections: Records from MAC addresses detected for more than 6 hours per day over 10 consecutive days were removed. Arrival and departure times were sorted chronologically, and round-trip durations were calculated to exclude likely residents or business users.

3. Duplicate Removal: Entries showing the same device at two locations simultaneously were identified and removed.

3.2.2 Sessionization

During the preprocessing phase, sessionization was applied by partitioning data on deviceid and ordering by timestamp, ensuring trajectory continuity even when user movements crossed the boundaries of defined temporal segments and thereby preventing information loss at transition periods. Connection data were organized into sessions grouped by deviceid, capturing the continuous connectivity of each user and identifying the specific siteid accessed within a given time frame. Each session was further subdivided using a one-minute time window to create fine-grained connection intervals, with timestamps converted into datetime format to extract the corresponding day and hour of each connection, as shown in Table 5. This structured approach enables chronological tracking of user movements, providing detailed insights into mobility patterns over time.

Table 5: Sample data of Chronological Sequence of User Connections by Day and Time.

timestamp	device id	site id	hour clock	day name
2023-05-22 15:05:19	277	1	15	Monday
2023-06-21 13:31:03	6492	3	13	Wednesday
2023-07-06 09:20:02	6536	6	9	Thursday
2023-08-27 11:43:09	739	9	11	Sunday
2023-09-13 18:26:06	690	7	18	Wednesday
2023-09-15 12:45:04	130	8	12	Friday
2023-09-21 17:54:18	481	2	17	Thursday
2023-10-01 02:03:47	432	4	2	Sunday
2023-10-14 09:24:38	242	5	9	Saturday
2023-10-18 08:12:32	808	10	8	Wednesday

3.2.3 Segmenting Data by Time Period

User movement behavior was analyzed by aggregating connection records from the same device within a session into transactions for ARM analysis. Simultaneous or closely timed connections were merged into a single transaction. Movements were segmented into four time periods for weekdays and weekends: 06:00–11:59, 12:00–12:59, 13:00–16:59, and 17:00–23:59. This segmentation enabled detailed examination of location interactions across different times of day, as illustrated in Table 6.

Table 6: Sample data of User Movements by Time Period 06:00 to 11:59 on Monday.

timestamp	device id	site id	hour clock	day name
2022-05-23 11:24:03	15	9	11	Monday
2022-06-06 08:11:04	561	6	8	Monday
2023-01-02 07:54:05	2552	4	7	Monday
2023-05-01 11:20:03	941	9	11	Monday
2023-03-27 09:30:06	3856	6	9	Monday

3.2.4 Sequence Creation

The aggregated data was formatted for ARM analysis, with each transaction comprising siteid, timestamp, deviceid, and sitename within the same session. Table 7 shows individual connection events, including deviceid, timestamp, and sequence of site transitions. For example, device 1088 first connected to site A9, followed by other sites in quick succession. This sequencing is essential for tracking movement patterns and generating association rules.

Table 7: Generate Sequential Movement Data for ARM.

device id	timestamp	Sequence Location
1088	2023-01-02 07:50:05	(Start, A9)
2659	2023-01-02 07:51:05	(A3,A4)
7340	2023-01-02 07:52:05	(A6,A7)
16386	2023-01-02 07:53:05	(A8,A7)
18161	2023-01-02 07:54:05	(A9,A9)
21715	2023-01-02 07:55:05	(A10,A11)

3.3 Association rule of co-occurring movement

To analyze tourist movement patterns, we utilized ARM through the Frequent Pattern Growth (FP-Growth) algorithm to discover relationships between movements across different locations along the Mekong River.

3.3.1 Quantification Measures

Our proposed analytical method for identifying potential routes relies on implementing the theory of ARM, a common technique in data mining for uncovering relationships between data sets. When applied to mobility patterns along the Mekong River, the ARM theory is instrumental in pinpointing the spaces that most frequently precede an event within a designated zone in Sri Chiang Mai. The significance of these ARMs is quantified using specific importance metrics to ascertain the most probable patterns. The indicators we employ to determine the strongest associations include [39].

- Support refers to the frequency with which an item-set appears in the dataset (movement between points A and B).

$$Support(\{A\} \rightarrow \{B\}) = \frac{\#movements\ A\ and\ B}{\#Total\ movements} \quad (1)$$

- Confidence refers to the frequency of being at point B after being at point A.

$$Confidence(\{A\} \rightarrow \{B\}) = \frac{\#movements\ A\ and\ B}{\#movements\ from\ A} \quad (2)$$

- Lift refers to the relationship between the overall movements from point A to point B, including all instances where A is the starting point. A value nearing 1 suggests that the occurrence of A and B is statistically independent of each other.

$$Lift(\{A\} \rightarrow \{B\}) = \frac{Confidence}{Support} \quad (3)$$

ARM is not limited to market basket analysis or strictly sequential events; it can also reveal co-occurring relationships without temporal order. Our study applies ARM to movement events occurring simultaneously or in proximate locations, enabling insights into spatial-temporal patterns that support traffic management, urban planning, and transportation policy development.

3.3.2 Implementation of FP-Growth Algorithm

The analysis employed the Standard FP-Growth algorithm within the Apache Spark MLlib distributed environment, which offers superior performance compared to Apriori for large datasets. Unlike newer non-distributed variants, this implementation ensures maximum stability and scalability for processing 73.7

million records, making it particularly well-suited for large-scale smart city applications. The algorithm creates an FP-Tree data structure to compress transaction data, reducing database scans to only two passes. The implementation was carried out using PySpark and the FPGrowth class from the `pyspark.ml.fpm` module, which required transforming the data into a suitable format using the `collect_set` and `struct` functions.

In this research, we set $\text{minSupport} = 0.2$ and $\text{minConfidence} = 0.1$ to obtain meaningful rules. The selected support value of 0.2 means that movement patterns must appear in at least 20% of all recorded movements, while the confidence value of 0.1 indicates that relationships must have at least 10% reliability. These thresholds helped filter out infrequent patterns or weak relationships, resulting in more concise and meaningful results.

3.3.3 Time-Based Analysis

To understand movement patterns across different times of the day, we divided the data into four time periods for both weekdays (Monday to Friday) and weekends (Saturday and Sunday):

Each 24-hour daily dataset was divided into four distinct periods:

1. Morning Time: 6:00 to 11:59.
2. Lunch Time: 12:00 to 12:59.
3. Afternoon Time: 13:00 to 16:59.
4. Evening Time: 17:00 to 23:59.

The temporal segments were defined based on local socio-economic activities: the morning peak of the Fresh Market (A9), the midday transition period, and the afternoon-to-evening shift toward recreation at the parks and courtyards (A5–A8).

3.3.4 Interpretation and Limitations

The mining results are presented as pairs of antecedent (source location) and consequent (destination location) with corresponding confidence and lift values to assess relationship strength. Lift values greater than 1 indicate a positive association, meaning that the presence of one location increases the likelihood of visiting another location.

However, the minimum thresholds set for support and confidence affect the number of rules discovered. A high support value might miss interesting but infrequent relationships, while an excessively low confidence value could lead to insignificant rules. Balancing these parameters is crucial for discovering meaningful patterns.

3.4 Analytical Tools and Software Implementation

We analyzed over 71.5 million Wi-Fi connection records (after deduplication) using Apache Spark for distributed processing. The workflow

was implemented in Jupyter Notebook with PySpark 3.9.2, enabling interactive data exploration and ARM. The Spark cluster comprised a master node (`spark://spark-master:7077`) and worker nodes configured with 1000MB executor memory, one executor core, and up to four cores per node.

Data preparation involved loading CSV files with schema inference, removing duplicates (reducing 73.7M to 71.5M records), casting timestamps to `TimestampType`, and extracting temporal features (hour and weekday) via Spark SQL functions. ARM employed MLlib's FP-Growth algorithm (`pyspark.ml.fpm`) with $\text{minSupport} = 0.2$ and $\text{minConfidence} = 0.1$, chosen for its scalability over Apriori. Analysis was segmented by time intervals (06:00–11:59, 12:00–12:59, 13:00–16:59, 17:00–23:59) and weekdays.

Sequence generation included:

1. Window functions to partition data by device ID and order by timestamp
 2. Custom UDFs (User-Defined Functions) to sort movement sequences chronologically
 3. Data transformation to capture transitions between locations using lag functions
 4. Aggregation to group movement patterns by device
- Results from the FP-Growth algorithm were exported to CSV format for further analysis and visualization, including metrics for support, confidence, and lift to evaluate the strength of discovered associations between locations.

3.5 Evaluation Metrics and Validation

Beyond the primary metrics of support, confidence, and lift described in section 3.3, additional evaluation methods were employed to validate the discovered association rules:

3.5.1 Statistical Significance Testing

Chi-square tests were performed on the discovered rules to determine statistical significance ($p < 0.05$), ensuring that identified patterns were not the result of random chance. This approach helped filter out rules that may have high confidence but lack statistical validity.

3.5.2 Cross-Validation Procedure

To validate movement pattern robustness, we applied time-based cross-validation by dividing the dataset into three non-overlapping periods and generating association rules for each. Rules appearing in at least two periods with similar metrics ($\pm 10\%$ variation) were deemed stable and included in the final analysis.

3.5.3 Practical Significance Assessment

Beyond statistical measures, we evaluated the practical significance of discovered rules by calculating the minimum improvement constraint (MIC) for

each rule. Rules with a lift value exceeding 1.5 were considered practically significant, indicating meaningful relationships beyond random co-occurrence.

3.6 Limitations and Constraints

Several limitations inherent to the dataset and methodology were identified and addressed:

3.6.1 Data Coverage Limitations

The analysis is constrained to users who connect to the public Wi-Fi network, potentially excluding tourists using mobile data or those without Wi-Fi-enabled devices. International tourists might be underrepresented due to their potential preference for roaming data services over public Wi-Fi.

3.6.2 Spatial Resolution Constraints

The 11 Wi-Fi access points provide discrete coverage along the Mekong River, leaving potential gaps in tracking continuous movement patterns. Movement tracking is limited to transitions between these fixed points rather than continuous path tracking.

3.6.3 Temporal Aggregation Effects

The division of data into four time periods (morning, lunch, afternoon, and evening) introduces temporal aggregation that may mask finer-grained movement patterns occurring within these periods. This aggregation was necessary for statistical reliability but potentially reduces temporal resolution.

3.6.4 Privacy Protection Trade-offs

The privacy protection measures implemented through MAC address anonymization and tokenization, while essential for ethical research, introduce a minor trade-off in tracking accuracy. The addition of random noise during the anonymization process slightly reduces the temporal precision of the dataset.

4. RESULTS AND DISCUSSION

The analysis of public Wi-Fi data using ARM in Sri Chiang Mai Municipality has unveiled significant patterns in user mobility, particularly regarding co-occurring movement events. This study, spanning from May 22, 2022, to December 31, 2023, leveraged data from 11 strategically positioned access points along the Mekong River. This comprehensive approach enabled the identification of key trends in user behavior across various times of day and days of the week.

4.1 Analysis of User Movement Patterns

Aligned with our objectives—understanding mobility patterns via Wi-Fi data, identifying temporal variations, evaluating ARM for analysis, and developing data-driven planning recommendations—our findings reveal distinct movement patterns. Public

Wi-Fi data analysis reveals clear differences in movement patterns between weekdays and weekends, with temporal variations across morning, midday, afternoon, and evening, and spatial concentration around commercial and leisure areas. Unlike prior studies using Bluetooth [32] or passive Wi-Fi sensing [28], this research examines long-term patterns in a riverside community.

Tables 8–14 use antecedents and consequents to detect successive movements. A frequent rule, $(\text{Start} \rightarrow \text{A9}) \rightarrow (\text{A9} \rightarrow \text{A9})$, shows high confidence (0.9908) and lift (1.6822) on Monday mornings, indicating users often start and remain at A9 (Fresh Market), while later periods shift toward leisure areas like A5 and A6.

Table 8: Results of Monday Movement Directions in 4 Time Periods.

Time Period	Antecedent →Consequent	Confidence	Lift	Support
06:00 - 11:59	$(\text{Start} \rightarrow \text{A9})$ $\rightarrow (\text{A9} \rightarrow \text{A9})$	0.9908	1.6822	0.0753
	$(\text{A9} \rightarrow \text{A9})$ $\rightarrow (\text{Start} \rightarrow \text{A9})$	0.7078	1.6837	0.0754
	$(\text{Start} \rightarrow \text{A9})$ $\rightarrow (\text{A9} \rightarrow \text{A9})$	0.9560	2.1156	0.1808
12:00 - 12:59	$(\text{A9} \rightarrow \text{A9})$ $\rightarrow (\text{Start} \rightarrow \text{A9})$	0.7146	2.1156	0.1808
	$(\text{Start} \rightarrow \text{A9})$ $\rightarrow (\text{A9} \rightarrow \text{A9})$	0.9796	1.8377	0.0017
13:00 - 16:59	$(\text{A5} \rightarrow \text{A6})$ $\rightarrow (\text{A6} \rightarrow \text{A5})$	0.9788	3.1209	0.0113
	$(\text{A5} \rightarrow \text{A6})$ $\rightarrow (\text{A6} \rightarrow \text{A5})$	0.9877	2.9131	0.0050

Mobility patterns observed on Tuesday closely resemble those of Monday with slightly more movement diversity. The Fresh Market (A9) remains dominant (confidence >0.95), while evening activity grows between Had Pathum Temple (A7) and Boeng Wiang Courtyard (A8 indicating their increasing significance as evening activity hubs).

Table 9: Results of Tuesday Movement Directions in 4 Time Periods.

Time Period	Antecedent →Consequent	Confidence	Lift	Support
06:00 - 11:59	$(\text{Start} \rightarrow \text{A9})$ $\rightarrow (\text{A9} \rightarrow \text{A9})$	0.9888	1.7314	0.0534
	$(\text{A9} \rightarrow \text{A9})$ $\rightarrow (\text{Start} \rightarrow \text{A9})$	0.7071	1.7123	0.0533
	$(\text{Start} \rightarrow \text{A9})$ $\rightarrow (\text{A9} \rightarrow \text{A9})$	0.9581	2.1496	0.1836
12:00 - 12:59	$(\text{A9} \rightarrow \text{A9})$ $\rightarrow (\text{Start} \rightarrow \text{A9})$	0.7191	2.1475	0.1834
	$(\text{Start} \rightarrow \text{A9})$ $\rightarrow (\text{A9} \rightarrow \text{A9})$	0.9831	1.8611	0.0275
13:00 - 16:59	$(\text{A5} \rightarrow \text{A6})$ $\rightarrow (\text{A6} \rightarrow \text{A5})$	0.6473	1.8618	0.0276
	$(\text{A5} \rightarrow \text{A6})$ $\rightarrow (\text{A6} \rightarrow \text{A5})$	0.9877	2.9532	0.0041
17:00 - 23:59	$(\text{A7} \rightarrow \text{A8})$ $\rightarrow (\text{A8} \rightarrow \text{A7})$	0.9852	3.5068	0.0037

On Wednesdays, Fresh Market (A9) shows the highest morning concentration among weekdays (confidence >0.99) with strong lunchtime retention (>0.96). Afternoon and evening patterns resemble Tuesday, with leisure movements between A5 and A8 (confidence >0.98).

Table 10: Results of Tuesday Movement Directions in 4 Time Periods.

Time Period	Antecedent →Consequent	Con- fidence	Lift	Support
06:00 - 11:59	(Start→A9)	0.9942	1.7113	0.0753
	→(A9→A9)			
	(A9→A9)	0.7286	1.7098	0.0752
12:00 - 12:59	→(Start→A9)			
	(Start→A9)	0.9634	2.1547	0.1808
	→(A9→A9)	0.7223	2.1584	0.1811
13:00 - 16:59	(A5→A6)	0.9825	3.1671	0.0138
	→(A6→A5)			
	(Start→A9)	0.9797	1.9094	0.0212
17:00 - 23:59	→(A9→A9)			
	(A5→A6)	0.9890	2.8909	0.0038
	→(A6→A5)			
	(A7→A8)	0.9854	3.5209	0.0031
	→(A8→A7)			

On Thursdays, Fresh Market (A9) dominates all day (confidence >0.94). Afternoon activity shifts between Community Health Park (A5) and Naga Courtyard (A6) (confidence = 0.98), while evening transitions between Had Pathum Temple (A7) and Boeng Wiang Courtyard (A8) remain stable (≈ 0.99), reflecting midweek leisure patterns.

Table 11: Results of Thursday Movement Directions in 4 Time Periods.

Time Period	Antecedent →Consequent	Con- fidence	Lift	Support
06:00 - 11:59	(Start→A9)	0.9946	1.7284	0.0073
	→(A9→A9)			
	(A9→A9)	0.6916	1.7284	0.0073
12:00 - 12:59	→(Start→A9)			
	(Start→A9)	0.9461	2.3020	0.1873
	→(A9→A9)	0.6806	2.3037	0.1874
13:00 - 16:59	→(Start→A9)			
	(Start→A9)	0.9848	3.3181	0.0147
	→(A6→A5)			
17:00 - 23:59	(A7→A8)	0.9805	1.9564	0.0228
	→(A8→A7)	0.9898	3.2803	0.0033
	(Start→A9)	0.9852	2.3698	0.0030
	→(A9→A9)			

Friday differs slightly from other weekdays; Fresh Market (A9) remains important in the morning and at lunchtime (confidence >0.94), while stronger afternoon movements occur between A5 and A6 (>0.98),

indicating a shift toward leisure. Evening transitions between A7 and A8 also stay high (>0.98), consistent with weekday patterns.

Table 12: Results of Friday Movement Directions in 4 Time Periods.

Time Period	Antecedent →Consequent	Con- fidence	Lift	Support
06:00 - 11:59	(Start→A9)	0.9927	1.735	0.0746
	→(A9→A9)			
	(A9→A9)	0.7119	1.737	0.0747
12:00 - 12:59	→(Start→A9)			
	(Start→A9)	0.9455	2.2353	0.1915
	→(A9→A9)	0.7219	2.2306	0.1911
13:00 - 16:59	(A5→A6)	0.9906	3.2338	0.0141
	→(A6→A5)			
	(Start→A9)	0.9747	2.0279	0.0196
17:00 - 23:59	→(A9→A9)			
	(A5→A6)	0.9882	2.8309	0.0028
	→(A6→A5)			
	(A7→A8)	0.9833	3.1884	0.0029
	→(A8→A7)			

Saturday exhibits distinct weekend patterns; Fresh Market (A9) remains significant from morning to afternoon (confidence 0.95–0.98), while evening movements between A7 and A8 (>0.98) and added activity between A5 and A6 reflect leisure-oriented behavior.

Table 13: Results of Saturday Movement Directions in 4 Time Periods.

Time Period	Antecedent →Consequent	Con- fidence	Lift	Support
06:00 - 11:59	(Start→A9)	0.9895	1.7729	0.0967
	→(A9→A9)			
	(A9→A9)	0.7332	1.7737	0.0967
12:00 - 12:59	→(Start→A9)			
	(Start→A9)	0.9523	2.2456	0.1401
	→(A9→A9)	0.7312	2.2445	0.1401
13:00 - 16:59	→(Start→A9)			
	(Start→A9)	0.9817	1.9829	0.0294
	→(A9→A9)	0.6253	1.9818	0.0294
17:00 - 23:59	→(Start→A9)			
	(A7→A8)	0.9864	3.0664	0.0024
	→(A8→A7)			
	(A5→A6)	0.9840	2.8148	0.0022
	→(A6→A5)			

Table 14 shows distinct Sunday patterns. Fresh Market (A9) functions as an all-day destination (confidence 0.83–0.98), while evening movement between Had Pathum Temple (A7) and Boeng Wiang Courtyard (A8) remains strong (>0.98).

Table 14: Results of Sunday Movement Directions in 4 Time Periods.

Time Period	Antecedent →Consequent	Con- fidence	Lift	Support
06:00 - 11:59	(Start→A9) →(A9→A9)	0.9884	1.7892	0.0976
	(A9→A9) →(Start→A9)	0.7272	1.7865	0.0975
12:00 - 12:59	(Start→A9) →(A9→A9)	0.9748	2.2321	0.1929
	(A9→A9) →(Start→A9)	0.7444	2.2333	0.1930
13:00 - 16:59	(Start→A9) →(A9→A9)	0.8351	1.9516	0.0727
	(A9→A9) →(Start→A9)	0.6269	1.9392	0.0722
17:00 - 23:59	(A7→A8) →(A8→A7)	0.9876	2.9877	0.0063
	(Start→A9) →(A9→A9)	0.9839	2.3999	0.0061

Daily mobility patterns in Sri Chiang Mai reflect socio-economic and cultural factors, including commercial activity near the Fresh Market, leisure use of parks and courtyards, religious practices around temples, and routine work schedules. Analysis reveals strong temporal and spatial trends: the Fresh Market (A9) dominates morning movements with high retention (confidence >0.95), while afternoons and evenings shift toward leisure spaces such as Community Health Park (A5) and Naga Courtyard (A6). Weekend-weekday variations, shaped by riverside settings and cultural practices, underscore localized dynamics. Evening transitions between leisure areas exhibit consistently high confidence (>0.98), indicating strong community engagement.

4.2 Smart City Policy Framework and Planning Implications

Based on the time-aware association rules discovered, this study proposes a Smart City Policy Framework for Sri Chiang Mai Municipality to optimize urban management through data-driven insights:

1. **Dynamic Resource Allocation:** The high morning connectivity at the Fresh Market (A9) (confidence > 0.99) indicates a need for time-specific municipal services. Instead of static management, the municipality should implement increased sanitation, waste collection, and security patrols specifically during the 06:00–12:00 peak hours to enhance urban livability.

2. **Temporal Safety Infrastructure:** The high-confidence leisure flows discovered between A7 and A8 in the evenings suggest a shift in urban space utilization. We recommend implementing temporary “Pedestrian-Only Zones” or activating “Smart Lighting” systems between 17:00 and 21:00 to support social safety and community engagement in these active zones.

3. **Data-Driven Decision Support:** This research demonstrates that public Wi-Fi infrastructure can function as cost-effective urban sensors. By utilizing the proposed ARM methodology, city planners can monitor infrastructure utilization and community engagement in real-time, allowing for evidence-based decisions in future smart city developments [37].

4.3 Comparative Analysis: Time-Aware vs. Time-Agnostic

To validate the necessity of temporal segmentation, we conducted a time-agnostic run (00:00–24:00) on the global dataset. As shown in Table 15, the ‘dilution effect’ is evident. The high-confidence pattern for the Fresh Market (A9), which shows a confidence of 0.99 in the morning, fails to meet the minimum support threshold in the agnostic model. This confirms that without time-aware segmentation, critical urban insights would be lost in the noise of global data.

Table 15: Comparative Analysis of Association Rules (Time-Aware vs. Time-Agnostic).

Mobility Pattern (Rule)	Time-Aware (Specific Period)	Time-Agnostic (Global 0-24h)	Impact of Temporal Context
(Start→A9) →(A9→A9)	0.9908 (Mon Morning)	Below Threshold	High: Pattern is only visible with time segmentation.
(A5→A6) →(A6→A5)	0.9906 (Fri Afternoon)	0.9709	Moderate: Pattern is stable but context adds precision.
(A7→A8) →(A8→A7)	0.9852 (Tue Evening)	0.9712	Stable: Confirms robustness of the sessionization.

5. CONCLUSION

This study leveraged public Wi-Fi data from 11 riverfront locations in Sri Chiang Mai to analyze mobility patterns and inform evidence-based urban planning. Access points deployed along the Mekong River enabled systematic tracking of device activity, identifying the Fresh Market (A9) as a primary mobility hub and revealing distinct temporal behaviors, across morning, afternoon, and evening periods, as well as notable weekday-weekend differences. ARM effectively uncovered movement associations, substantiated by high confidence and lift values. Crucially, the comparative analysis demonstrated that the proposed time-aware model consistently outperforms time-agnostic approaches in capturing period-specific behaviour’s, such as market-driven mobility, which are essential for responsive and adaptive smart city planning.

These findings informed a series of targeted urban interventions, including traffic management measures, shade structures, seating enhancements, landscape improvements, and upgraded nighttime lighting. High-activity nodes—namely the Community Health Park (A5), Naga Courtyard (A6), and Boeng Wiang Courtyard (A8)—were identified as critical anchors for connectivity and crowd management. Although public Wi-Fi data provides valuable behavioural insights, its inherent limitation of excluding non-Wi-Fi users should be acknowledged. Future research should therefore integrate multimodal data sources, including GPS trajectories, mobile network data, and social media signals, alongside advanced machine learning techniques to further refine mobility models and enhance predictive capabilities.

Overall, this study demonstrates the substantial potential of public Wi-Fi data as a foundation for data-driven urban planning, contributing to safer, more connected, and sustainable riverfront communities.

DATA AVAILABILITY

The dataset comprises anonymized Wi-Fi logs from 11 public access points in Sri Chiang Mai Municipality, Thailand, collected between May 22, 2022, and December 31, 2023. It is publicly available via Figshare (<https://doi.org/10.6084/m9.figshare.23691336.v11>). Data were anonymized using SHA-256 encryption and tokenization. This study received ethical exemption from the Khon Kaen University Ethics Committee (Ref. HE653311). Users should cite this dataset and adhere to the associated ethical guidelines.

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AUTHOR CONTRIBUTIONS

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