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A Simplified Approach to Big Data Applications in Tourism: Monitoring Weekly Visitor Patterns of a Heritage Site Using Google Popular Times

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Abstract

This study introduces a simplified big data application approach to monitor weekly visitor patterns in the example of heritage sites using semi-structured data. A descriptive research design was adopted by employing exploratory data analysis on hourly visitor intensity data retrieved from Google's Popular Times feature to monitor weekly visitor patterns in the case of Beylerbeyi Palace, Istanbul. Data were collected between March and April 2025. Visitor patterns were identified through systematic graphical analysis and validated by quantitative indicators, including measures of central tendency and slope values of intensity curves. The results revealed six distinct visitor patterns that included weekday low peak, weekend high peak, morning low intensity, afternoon high intensity, positive slope, and negative slope, capturing both daily and weekly levels. Instead of employing complex analysis, by applying a novel approach to a single heritage site as a pilot study, it provides preliminary evidence that semi-structured big data can be effectively used to monitor visitor patterns in a cost-efficient and replicable way and emphasises the practical usefulness of a simple, digitally supported method for tracking visitor activity. Future studies could expand this preliminary approach to multiple sites or integrate it with AI-based analytical tools to improve pattern identification and support visitor flow prediction or management strategies.

Keywords Visitor Monitoring · Big Data in Tourism · Visitor Pattern Analysis · Heritage Sites · Google Popular Times

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1. Introduction

Sustainability is one of the most important challenges of our world. As digital transformation continues to advance, concerns about the use of the world's limited resources have increased. There are ongoing debates about whether information technologies, especially big data and AI-based systems, consume too many resources (Bolon-Canedo et al., 2024; Garrigos-Simon et al., 2021; Etzion and Aragon-Correa, 2016). Finding ways to use data-driven applications more efficiently is now essential. A major research challenge lies in developing simpler approaches that can help reduce the resource demands of technology while maintaining its practical value (Al-Jarray et al., 2015; Adadi, 2021; Zong and Guan, 2025).

As technology continues to advance, the tourism industry increasingly uses data-driven approaches to understand visitor behaviour and manage destinations more effectively (Nag and Mishra, 2024; Guerard et al., 2024; Chen et al., 2021; Norouzi et al., 2022). The growth of big data is changing the way tourism activity is observed and interpreted. It allows researchers and tourism managers to follow visitor movements more closely, analyse them in real time, and make decisions based on solid evidence. Information gathered from digital footprints, mobile apps, and online platforms helps reveal where, when, and how tourists engage with touristic sites, which is crucial for developing personalised tourism products or improving visitor experience.

Monitoring visitor intensity is particularly important for heritage sites, where capacity is limited and preservation concerns restrict infrastructure changes (Phillips, 2015). Fluctuations in tourist numbers directly affect both visitor experience and conservation (Goulding and Pomfret, 2022). Methods like manual monitoring or using ticket records can miss short-term changes in visitor numbers since they exclude people who visit without buying a ticket or leave unrecorded. Big data, by contrast, offers a useful way to track these patterns and understand how visitors flow shifts over time (Reif and Schmucker, 2020; Miah et al., 2019).

Among these sources, Google's Popular Times provides continuous and detailed information about visitor activity (Mahdi et al., 2023). This dataset qualifies as big data since it is generated from millions of mobile signals worldwide (Google, 2025). However, because Google processes and normalises these data into a user-friendly format, the final output is simplified and publicly accessible. Thus, Popular Times data can be seen as a practical source for developing simplified big data approaches. Accessing big data usually requires expensive sensor systems or complex data collection methods. At the same time, analysing this kind of dataset often requires advanced analytical expertise (Djedouboum et al., 2018; Fan et al., 2014). To make these tools more practical and accessible for small-scale monitoring, simplified approaches can effectively identify short-term visitor patterns.

The rationale for adopting a simplified approach is grounded in both the structural realities of the tourism industry and the principles of sustainability. Tourism exists in a wide variety of fields, including heritage sites, museums, natural areas and includes many small businesses (Camilleri, 2017). Particularly for heritage sites, implementing traditional monitoring systems or advanced predictive analytics presents significant operational challenges due to limitations in technical capacity, budget, and specialised human resources. Furthermore, although advanced algorithms aim for precision under controlled conditions, their rigid structures may not always be seamlessly adaptable to the variable nature of practical, everyday data. (Tukey, 1977; Hoaglin et al. 2000; Perer and Shneiderman, 2008). Using existing big data through a simplified approach can also help reduce resource consumption, contributing to sustainability.

At the same time, since this study works on a semi-structured dataset (Google Popular Times) whose structure is not yet fully known, instead of moving directly to complex models, it is considered useful to first adopt an exploratory approach, which makes it possible to understand the natural structure and patterns of the data. As Tukey (1977) also stated, exploring the structure of data before conducting hypothesis tests is the most fundamental step of scientific analysis. Moreover, since the semi-structured dataset used in this research is already pre-processed and normalised by Google, adopting a simplified exploratory approach is appropriate and meaningful for the aims of this study. In this respect, the study has a preliminary nature.

The literature on big data has predominantly focused on advanced techniques; however**,** a significant "applicability gap" remains, particularly for tourism. The primary contribution of this research is to bridge this gap by proposing a simplified, practically applicable framework. The novelty of this study lies in its innovative use of pre-existing, semi-structured Google Popular Times (GPT) data as a cost-effective monitoring tool. This line of reasoning leads to the aim of this study, which is to demonstrate how a simplified big data application can be used to monitor visitor patterns in tourism, particularly within heritage sites. This practical approach can serve as a cost-effective and simple way to monitor visitor patterns and support data-based decisions, contributing to data applications in tourism.

2. Literature Review

Big data mean large and complex data that traditional software cannot manage (Laney, 2001). It can be collected from many digital sources, such as sensors, phones, or social media (Marr, 2016). Big data is often described with five features: volume, velocity, variety, veracity, and value (Furht and Villanustre, 2016). This shows that data is large, fast, diverse, needs to be trusted, and must create benefit. Big data is essentially characterised by the sheer variety of data it includes which researchers commonly separate into structured, semi-structured, and unstructured forms (Oussous et al., 2018; Gandomi and Haider, 2015).

The data used in this study, the Google Maps' Popular Times (GPT) feature, can be seen as an example demonstrating the nature of semi-structured big data in practice. This information, generated through the processing of massive, anonymized signals from mobile devices, typically presents its findings in a JSON-based structure. This format effectively acts as a bridge, integrating structured data, such as the calculated percentages for hourly visitor intensity, with necessary unstructured metadata, such as the business's name and specific category (Google, 2025).

In tourism studies, big data helps to see what happens in real time and plan better. Big data can also support visitor monitoring and help managers understand how people use a site (Yang et al., 2018). Monitoring is the systematic and periodic measurement of key indicators of biophysical and social conditions to evaluate progress towards management or planning objectives (Eagles et al., 2002). In other words, visitor monitoring basically means recording and studying how many people visit a place, when they come, and what they do (Arnberger et al., 2005; Cessford and Mugar, 2003).

Eagles et al. (2002) divided monitoring into two main types. The first is visitor impact monitoring, which involves regularly measuring and evaluating the environmental and social effects of visitors. The second is service quality monitoring, which examines how well visitors' needs and expectations are being met. Visitor monitoring is traditionally based on global positioning systems (GPS) and detectors or specific sensors. GPS enables spatial and temporal tracking of visitors through satellite data. Detectors and sensors are used to count and monitor visitor flow (Arrowsmith et al., 2005; Muhar et al., 2002). Monitoring helps managers address crowding, safety, and conservation. The main goal is to provide useful information for the sustainable planning and daily management of visitor flows. Monitoring visitor flow, especially in natural areas and heritage sites, is vital for effective management that balances recreation and conservation (Orellana et al., 2012; McKercher and Lau, 2008).

Heritage sites describe places of cultural, historical, natural, or scientific importance that preserve the past and help people stay connected to their history (UNESCO, 1972; Cleere, 2011). Ancient ruins, historic cities, monuments, and cultural landscapes are included in this definition. While some heritage sites are officially listed by UNESCO as World Heritage Sites, many others are not on that list but are still protected at national or local levels. Even without UNESCO recognition, these places are important and need proper care and management to preserve their value for future generations (Timothy and Boyd, 2003; Smith, 2006).

To protect these places, the management of these areas must know how people visit and move inside them. Visitor patterns generally show how and when tourists visit a place over different periods. Tourism research includes several related concepts, such as visitor behaviour patterns, visitor movement patterns, and visitor flow patterns (Orellana et al., 2012; Kuflik et al., 2012; Strohmaier et al., 2015). Each refers to how visitor activity changes across space and time. Behaviour patterns describe how visitors act and what they focus on during a visit. Movement patterns show where they go, how long they stay, and the routes they follow within a site. Flow patterns represent how the number of visitors increases or decreases at certain times, forming daily or weekly cycles (Bitgood, 2006; Yoshimura et al., 2014; Zancanaro et al., 2007). Since GPT provides a simplified and normalised picture of visitor intensity, this study uses the general visitor patterns term to describe these temporal and spatial regularities in a concise way.

Recent studies show that monitoring is crucial for protecting heritage sites. Fletcher et al. (2007) showed that monitoring in the Angkor site used GIS maps to watch changes in the area. They also worked with local people to plan how to protect and use the site. Gribaudo et al. (2018) used an Internet of Things (IoT) monitoring system in Matera, Italy. Many sensors were placed around the site to check light, humidity, and movement in real time. Gullino et al. (2015) studied rural World Heritage Sites and said that monitoring should include both nature and people. They showed that checking social and environmental data helps make better decisions. Zhou et al. (2015) used radar interferometry to monitor the ground and build changes in heritage areas. Their method can find very small movements and warnings before damage happens.

There are also studies that use big data to understand travel and visitor patterns in tourism. Shi et al. (2021) used large car-hailing data to monitor travel inside the city. Their study showed that travel distance stays almost the same each day, but travel time and speed change with weather and weekday patterns. This means that city travel has clear time-based rhythms. Reif and Schmucker (2020) used mobile phone data to study where and when people move in tourism areas. They found that these big data help see general visitors' flows and patterns. However, it is still difficult to know who a tourist is and who is a local person. Both studies show that big data can help find movement patterns and understand how people travel, but it also needs careful use to get the correct results.

Publicly available digital data have only recently been used as a big data source in monitoring tourism. Fuchs et al. (2021, 2025) showed that Google Maps data can be used for real-time monitoring and sentiment-based analysis of cultural tourism sites in Sweden, offering a powerful yet still underused tool for destination intelligence. However, they focus more on user generated content on Google Maps. There are also studies that specifically focus on GPT data. Vongvanich et al. (2023) found that GPT can help predict how busy stations will be and which nearby places affect traveller flow. Mahdi et al. (2023) investigated how long people stay at points of interest. They found that place type, transport access, and location explain most of the visit time. Milea et al. (2022) looked at how GPT can help in health studies. They showed that it reflects how people move and gather, which can help track disease spread. Castiglione et al. (2024) joined car movement data with GPT to study travel flexibility. They found that work trips are more fixed, whereas leisure trips change more in time and space. Barrena-Herran et al. (2025) used machine learning on GPT data to find city activity patterns. They found that each area has its own daily rhythm depending on land use. Santiago-Iglesias et al. (2023) used it to study how a snowstorm changed city life in Madrid. They found that basic needs were less affected than leisure activities. Prasetyani et al. (2023) found clear time-based patterns that can help improve road planning.

All these studies demonstrate that Google Popular Times (GPT) data has been used as a reliable source across diverse fields in recent years, ranging from public health and urban management to climate change and tourism. However, research specifically focusing on GPT data within the context of tourism, despite its high potential, remains quite limited. Furthermore, most of the literature generally proceeds at an urban or large-scale level or requires complex analytical methods. Yet, GPT data are publicly provided separately for each individual tourist heritage site. These data hold significant potential for determining visitor patterns, even for micro-businesses or localised areas. This reveals a major research gap because even though these existing methods offer innovative solutions, they are often too difficult to apply in practice. In a diverse sector like tourism, involving many small entities such as museums, heritage sites, restaurants, and cafes, implementing and analysing these complex methods can become simply too expensive and challenging.

From this research gap, this study aims to present a simplified approach tailored specifically to the tourism scale. In doing so, it demonstrates how semi-structured big data can be used for monitoring and how visitor patterns can be identified cost-effectively using a simplified approach. This approach represents a novel contribution to the literature. For this reason, the approach is applied to a single heritage site as a pilot application to test the results.

3. Methodology

3.1. Research Design

This study uses a descriptive research design with quantitative secondary data derived from Google Maps. Descriptive research focuses on explaining a population or phenomenon by addressing "what," "where," and "when," rather than exploring the reasons behind it (Balnaves and Caputi, 2001; Ghanad, 2023; Solomon and Draine, 2010). Accordingly, five independent weekly datasets collected for the Beylerbeyi Palace between March 2025 and April 2025 were analysed within an exploratory data analysis (EDA) framework (Tukey, 1977). Exploratory data analysis focuses on examining data in a flexible way before applying any probabilistic model. As Tukey (1977) highlights, the purpose of EDA is to look closely at the structure of the data, reveal patterns and anomalies, and guide researchers towards meaningful insights without relying on strict assumptions.

The EDA protocol was applied through a systematic procedure tailored to the dataset's nature. Since the data were already normalised and consisted of a single variable (visitor intensity), this simplified protocol was considered sufficient to capture meaningful insights without requiring advanced multivariate techniques. The process followed these steps: First, in the data integrity and pre-processing step, the dataset was examined for structure and missing values. Hourly intensity values (0–100) were filtered to retain only observations within operating hours (09:00 - 17:30) and the five weekly datasets were averaged to generate a single representative weekly profile. Secondly, in descriptive summarisation step, measures of central tendency were calculated to provide a concise overview (Gravetter et al., 2021). Then, in basic visualisation step, distribution charts were created to visualise density patterns.

Lastly, the pattern identification step was conducted in two distinct stages. Initially, the graphs were visually analysed to identify recurring temporal regularities through distribution charts. As Perer and Shneiderman (2008) noted, linking statistics and visual representations strengthens exploratory data analysis; therefore, these visual observations were quantitatively validated using descriptive indicators: slope direction was used to confirm trend stability (for patterns S1, S2), visitor intensity ratios across different daytime categories were used to verify daytime density variations (for patterns H1, H2), and the difference in peak values was verified by comparing the superimposed average distributions of weekdays and weekends (for patterns W1, W2). This combined approach ensured that the identified patterns were not subjective impressions but reproducible structures grounded in transparent analytical criteria.

3.2. Data Collection

The data were systematically collected from Google Maps' Popular Times feature for Beylerbeyi Palace using the official Google Places API, in compliance with Google's terms of service. The dataset covers one full week of hourly visitor intensity values, normalised on a 0–100 scale, across five separate observations. In this dataset, the busiest hour of the week is considered as 100, and all other values are scaled accordingly.

To ensure data consistency and minimise temporal discrepancies, the data extraction process was performed through an automated script developed in Python. Since the platform does not archive historical live data for retrospective retrieval, real-time data acquisition was mandatory. Therefore, the developed script was executed at five distinct intervals to obtain five separate weekly datasets. This procedure involved retrieving the JSON-formatted intensity data for the specific "Place ID" of the heritage site.

Google's Popular Times (GPT) is a Google Maps feature that estimates hourly visitor intensity based on aggregated and anonymized location data from users who have enabled location services. In other words, it shows how busy a site typically is at different times of the day throughout the week (Google, n.d.). Since the GPT data are based on the average business activity over the last few months and collected from thousands of mobile location signals, it carries the characteristics of semi-structured big data (Google, n.d.).

3.3. The Sample

Beylerbeyi Palace was purposefully selected as the research site due to its distinct spatial position and suitability for pattern observation. Purposive sampling enables the intentional selection of a case that is particularly relevant to the research objectives. However, this method naturally limits the extent to which the findings can be generalised (Patton, 2002).

Beylerbeyi Palace is located on the Asian Side of Istanbul, and the palace is geographically separated from the city's main cluster of tourist attractions concentrated in the Historical Peninsula and European districts (National Palaces Administration, 2025). Beylerbeyi Palace's location, separated from Istanbul's main tourist cluster, offers a clearer setting to observe how visitors' intensity changes over time without interference from nearby attractions. The palace itself is a heritage landmark that embodies the architectural and cultural heritage of the late Ottoman Period. Built in the nineteenth century as a summer residence and a guesthouse for state visitors, it now serves as a preserved cultural site reflecting distinctive Ottoman design elements within Istanbul's historical fabric (National Palaces Administration, 2025).

In addition, the site's operating hours (09:00–17:30, during observation months) and consistent data availability through the GPT feature allowed systematic hourly observation and reliable temporal comparison. For these reasons, Beylerbeyi Palace was considered an appropriate pilot case for testing the applicability of a simplified approach to visitor monitoring with a big data source, enabling the identification of temporal patterns in visitor intensity.

3.4. Assumptions and Limitations

The data obtained from Google's Popular Times represent relative intensity, not actual visitor counts. Values are normalised on a 1–100 scale, where 100 indicates the highest observed activity during the week and does not correspond to any real number or percentage.

The identified patterns are derived from the descriptive interpretation of central tendency measures and visualised distributions, not from advanced statistical or algorithm-based pattern recognition methods. The dataset reflects the general density around the site, not exact entrance or exit figures. Therefore, the findings indicate temporal activity patterns rather than total visitation. Finally, the study relies on five separate weekly observations from a single site, which limits the generalisation of results to other contexts or time periods.

4. Findings

4.1. Descriptive Overview of the Dataset

The descriptive statistics of data presented in Table 1 summarise the temporal structure of visitor intensity across five separate observations. Each observation originally contained 168 (7 × 24) hours of data retrieved from Google's Popular Times; however, since the selected heritage site operates only six days per week and for eight hours per day (09:00-17:30), each observation includes 48 meaningful hourly records. The dataset represents normalised visitor intensity values on a relative scale ranging from 0 to 100, where 100 indicates the peak hourly intensity within the observed week. These standardised values provide a consistent basis for comparing daily and weekly temporal variations in visitor activity.

Table 1

Descriptive statistics of temporal visitor intensity observations

Observation	N	Min	Max	Mean	Median
O_1	48	14	100	51.06	53.50
O_2	48	15	100	51.15	53.00
O_3	48	14	100	51.02	53.50
O_4	48	16	100	52.20	55.50
O_5	48	16	100	52.56	53.00
Overall	**240**	**14**	**100**	**51.66**	**53.00**

Table 1 shows that visitor intensity descriptives across the five observations are highly similar. The five observations were collected from separate weeks within a two-month period, their similarity is therefore expected. This indicates the consistency of the dataset and confirms that the results are stable across time.

4.2. Observational Findings

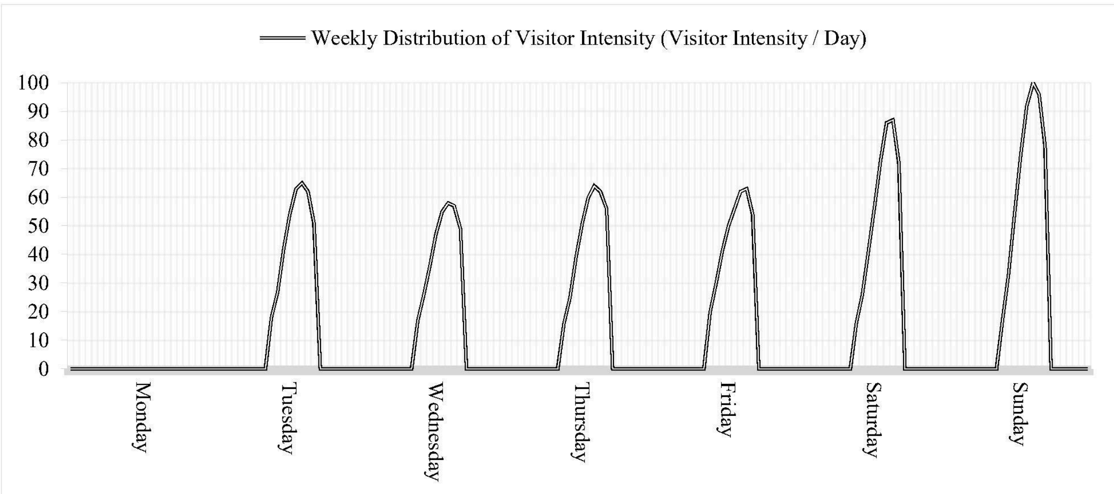
Weekly Distribution of Visitor Intensity

To provide a general picture of the distribution, Figure 1 presents the weekly visitor intensity distribution obtained by averaging five separate observations. From this point onward, all analyses are conducted using these average values, as shown in Figure 1 and Figure 2. The line chart shows normalised hourly data (0–100 scale) across the week.

Since the site remains closed on Mondays, visitor activity takes place only during the six operational days. The distribution reveals nearly consistent daily peaks from Tuesday to Friday. This indicates the first signs of a recurrent weekly pattern in visitor flow.

Figure 1

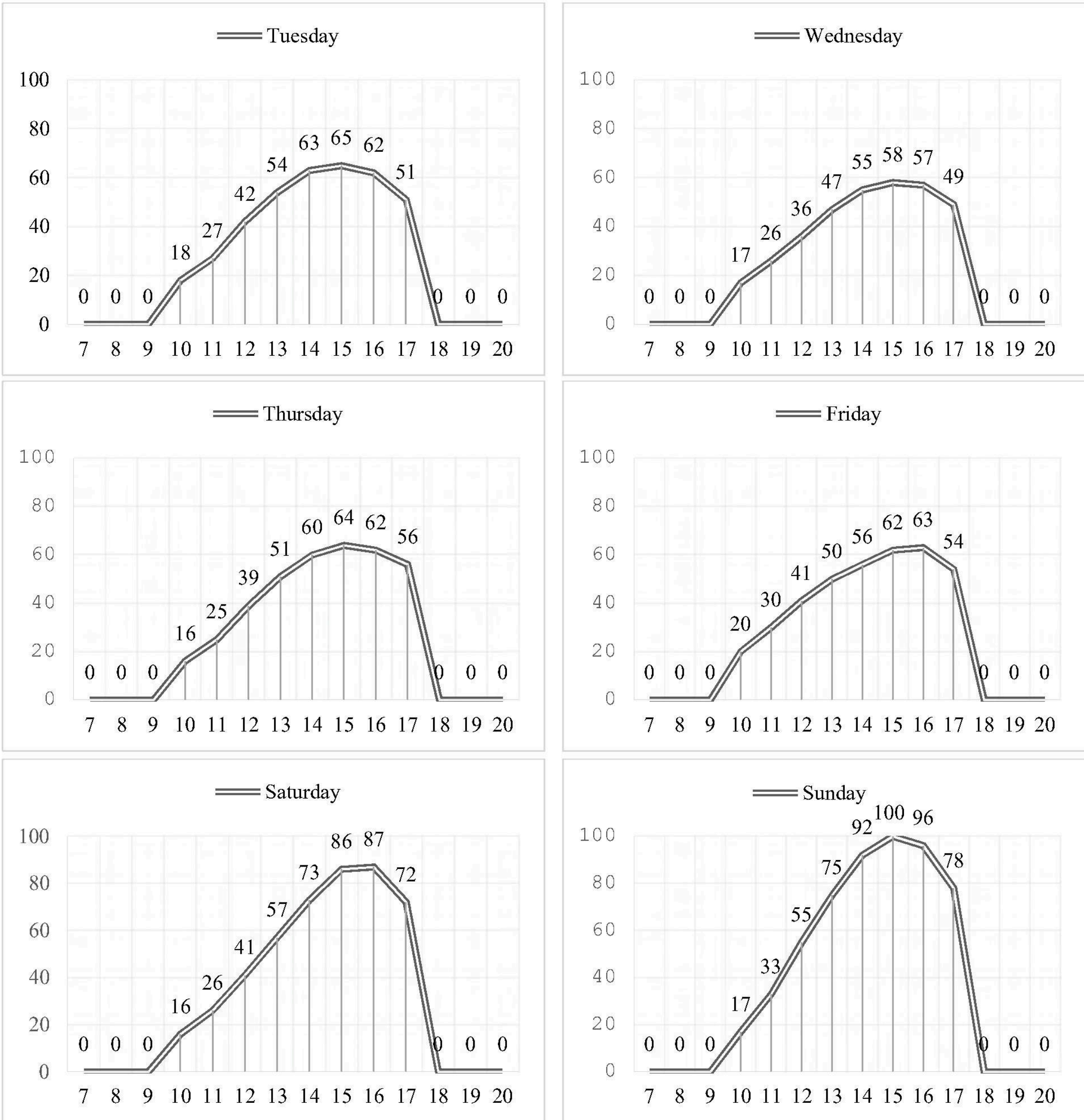
Weekly distribution of visitor intensity



Daily Distribution of Visitor Intensity

Focusing on the temporal dynamics observed within each day, Figure 2 presents the daily visitor intensity distribution for the six operational days. Each curve illustrates the daily rhythm of visitor activity. It usually shows a gradual increase in the morning hours, a pronounced peak around midday, and a subsequent decline towards closing time. When viewed together, the six daily charts give one earlier sign of a recurring daily pattern in visitor flow.

Figure 2
Daily distribution of visitor intensity throughout the week (visitor intensity/hour)

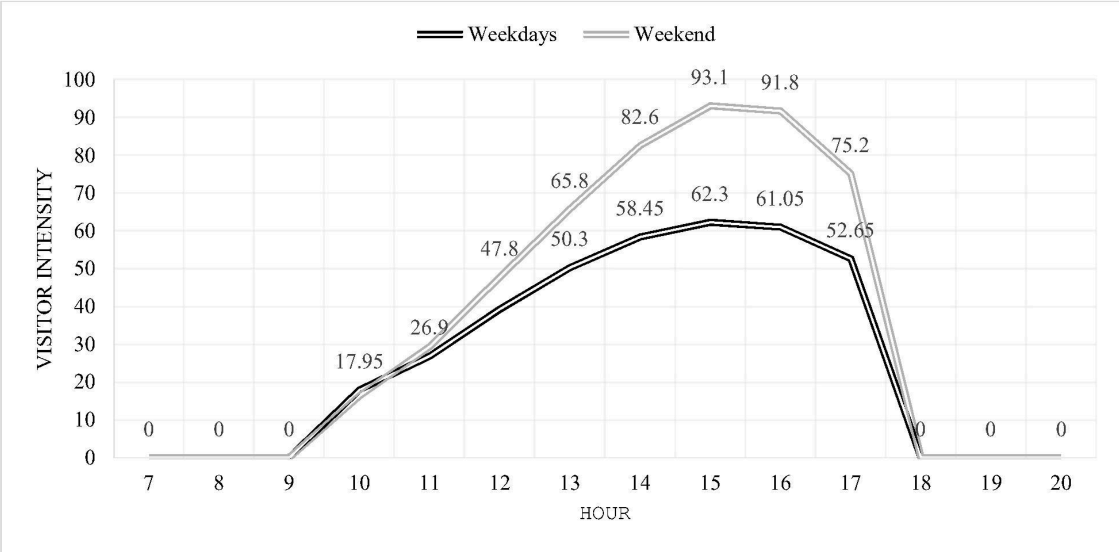


4.3. Identified Temporal Patterns

Based on Figure 1 and Figure 2, similar temporal regularities were observed across weekly and daily dimensions. The analysis first indicated that visitor activity displayed two distinct but internally consistent patterns throughout the week, with relatively similar distribution shapes repeating during weekdays and a separate, more intense pattern during weekends. Similarly, similar intensity patterns were detected across different time intervals within the day. The third observed pattern indicated that the direction of intraday intensity changes remained consistent across all days of the week. These observations across weekdays and weekends and hourly dimensions provided the conceptual basis for pattern identification.

Figure 3

Comparative distribution of weekdays and weekend visitor intensity



When the two temporal dimensions were overlaid and examined together, as shown in Figure 3, the comparative visualisation of average weekday and weekend visitor flows revealed two dominant weekly patterns. The first pattern corresponds to weekdays, showing relatively stable intensity levels with lower peaks across weekdays. The second pattern represents weekends, characterised by higher and more concentrated midday activity. page

Figure 4

Comparative distribution of hourly visitor intensity throughout week

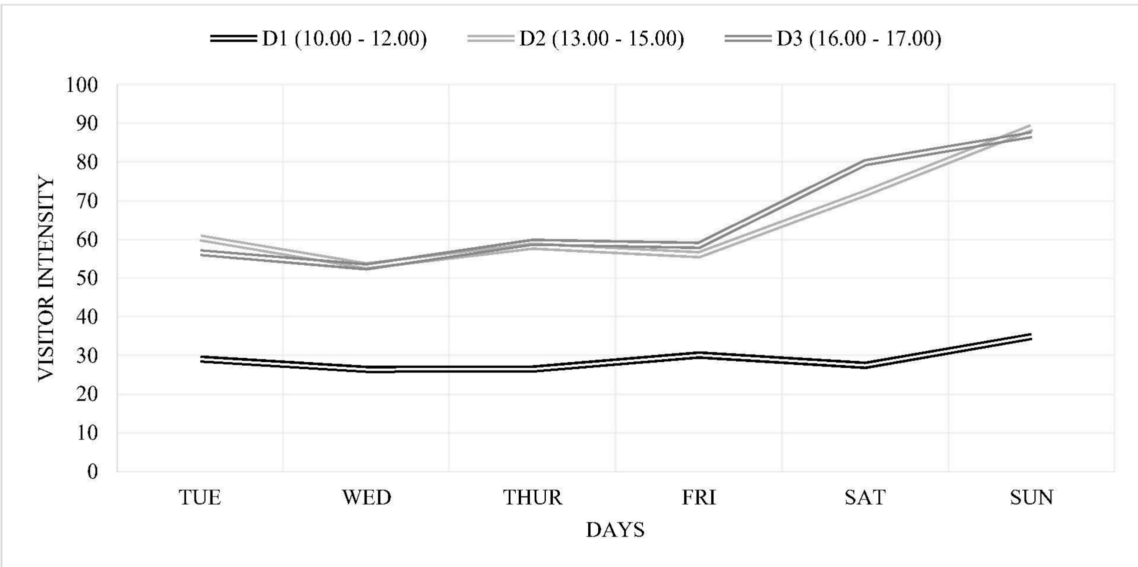


Table 2

Visitor intensity ratios across weekdays by daytime categories

	TUE	WED	THU	FRI	SAT	SUN
D2/D1	2.08	2.02	2.20	1.86	2.62	2.55
D3/D1	1.95	2.01	2.23	1.94	2.91	2.49
D2/D3	1.07	1.00	0.98	0.96	0.90	1.02

Similarly, as illustrated in Figure 4 and shown in Table 2, the analysis of average intraday variations revealed two additional patterns reflecting hourly concentration trends. The first indicates nearly overlapping intensity distributions between D2 (13:00–15:00) and D3 (16:00–17:00) hours, where visitor density remains at similar levels (D2/D3 ≈ 1.0). The second corresponds to the morning hours, which exhibit a distinct distribution, with intensity values roughly half those of midday and afternoon periods (D2/D1 ≈ 2.0 across all days) falling even lower during the weekend (D2/D1 ≈ 3.0 across the weekend).

Figure 5

Comparative distribution of hourly visitor intensity by slope direction

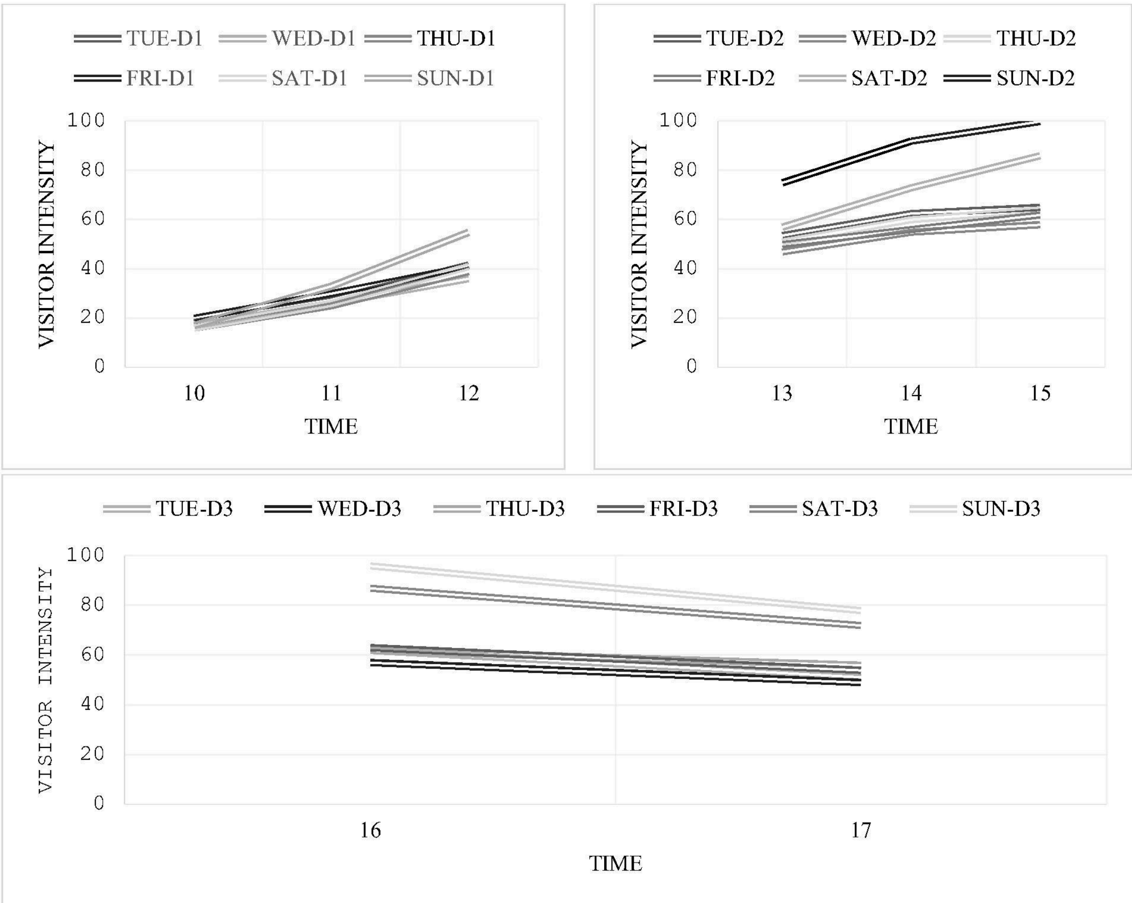


Table 3

Slope values of visitor intensity across weekday and daytime periods

	CAT	TUE	WED	THUR	FRI	SAT	SUN
m (10–11)	D1	9.2	9.0	9.0	10.0	10.0	16.0
m (11–12)	D1	14.2	10.0	14.0	11.0	15.0	22.0
m (13–14)	D2	9.0	8.0	9.0	6.0	16.0	17.0
m (14–15)	D2	2.4	3.0	4.0	6.0	13.0	8.0
m (16–17)	D3	−10.8	−8.0	−6.0	−9.0	−15.0	−18.0

The third identified pattern type is direction oriented as shown in Figure 5. On a daily and hourly basis, a similar directional tendency was observed for all days of the week. As shown in Table 3, slope values for D1 (10:00–12:00) and D2 (13:00–15:00) remained positive ($m > 0$) across all days, indicating a consistent upward trend in visitor intensity. In contrast, D3 (16:00–17:00) displayed negative slopes ($m < 0$) for every day, representing the downward phase towards closing hours.

When analysed collectively, based on exploratory analysis, six temporal patterns (W1, W2, H1, H2, S1, and S2) were identified, representing weekday - weekend differences and hourly concentration and direction trends, as shown in Table 4. Patterns were identified through the visual interpretation of daily and weekly visitor intensity distributions shown in Figure 1 and Figure 2 and were further supported by Figure 3, Figure 4, and Figure 5 as well as quantitatively validated using the descriptive indicators presented in Table 2 and Table 3.

Table 4

Identified visitor flow patterns

Code	Type	Identified Pattern	Description
W1	Weekly Basis	*Weekday Low Peak Pattern*	Represents relatively stable intensity levels with lower peaks across weekdays.
W2	Weekly Basis	*Weekend High Peak Pattern*	Represents relatively higher peaks and more concentrated midday intensity across weekends.
H1	Daily Basis	*Morning Low-Intensity Pattern*	Represents relatively lower visitor intensity during morning hours compared to the rest of the day.
H2	Daily Basis	*Afternoon High Intensity Pattern*	Represents relatively higher and peak visitor intensity from midday to late afternoon compared to morning hours.
S1	Daily Basis	*Positive Slope Pattern*	Represents a consistent upward trend in visitor intensity during morning and midday hours.
S2	Daily Basis	*Negative Slope Pattern*	Represents a consistent decline in visitor intensity from midday towards closing hours.

The six identified patterns categorise the visitor density profile at Beylerbeyi Palace, as shown in Table 4. Patterns W1 and W2 represent density trends that are distinctly separated between weekdays and weekends. When the graphs of weekday and weekend density distributions are overlaid, it is seen that weekdays at Beylerbeyi Palace have almost the same density pattern; hence, this distinction has been made. On the other hand, weekends have a different density pattern that reaches a high peak.

Visitor patterns were also examined daily according to the hourly distribution within the day. One of the most important findings is that morning hours are relatively less busy than midday and afternoon hours throughout all 7 days of the week without exception. This distinction is concretised in Table 2, as statistically supported, resulting in the creation of H1 and H2 patterns. The H1 pattern is valid for all 7 days of the week, representing a pattern where morning hours are 2 to 3 times less intense than the remaining hours of the day. H2, on the other hand, represents the high density pattern that emerges during the day, particularly in the afternoon and thereafter.

Direction is also quite important in determining visitor patterns. This is because direction-based patterns could provide insights for management applications and for making temporal predictions. At Beylerbeyi Palace, the linear slope of the hourly intensity curve between each two-hour period was examined separately in Table 3, and the direction of intensity was statistically supported. The analysis identified the S1 and S2 patterns. S1 represents the consistent increase in intensity during the morning and afternoon hours. S2 is the pattern representing the decrease in intensity from the afternoon until closing time. It is seen that these two patterns are repeated for all 7 days of the week.

The six identified patterns indicate that visitor intensity at Beylerbeyi Palace shows distinct temporal density variations across both daily and weekly bases. Monitoring and identifying these foundational patterns represent an essential preliminary step towards interpreting and managing visitor intensity more effectively within heritage environments.

5. Discussion and Conclusion

This study demonstrates how semi-structured big data can be used for monitoring visitor density and identifying weekly visitor patterns in tourism, specifically in heritage sites with a simplified approach by applying to a single tourist heritage site as a pilot application. This study identified six different visitor flow patterns, both weekly and daily temporal dimensions. These patterns reveal that visitor intensity at Beylerbeyi Palace follows some consistent trends. Monitoring and identifying such foundational patterns represent an essential preliminary step towards interpreting and managing visitor flow more effectively within heritage environments.

Big data analysis is typically associated with large-scale, complex computational processes that demand technical expertise and costly infrastructure (Laney, 2001; Furht and Villanustre, 2016). In contrast, this study proves that a simplified approach on semi-structured big data, such as Google's Popular Times, can enable cost-effective and easily replicable monitoring, filling the research gap by bringing practical novelty. In previous studies, big data has been used, particularly in some cases through Google Popular Times, for real-time monitoring, developing user content-based predictive models, analysing urban-scale movements, and identifying activity patterns within city areas (Fuchs et al., 2025; Vongvanich et al., 2023; Mahdi et al., 2023; Milea et al., 2022; Castiglione et al., 2024; Barrena-Herran et al., 2025; Santiago-Iglesias et al., 2023). However, this study advances the literature by proposing a practical, cost-effective, and more sustainable approach. Furthermore, research on big data applications in the field of tourism is still limited and developing. It presents a simplified micro-scale approach to visitor monitoring, which aligns well with the predominantly small-scale nature of tourism enterprises.

This is particularly valuable for small museums or local heritage attractions where resource limitations hinder the adoption of advanced monitoring systems. Hence, the proposed approach bridges the gap between complex big data analysis and practical monitoring needs in tourism. The patterns found in this study may seem predictable at first. However, the main value of the research is in showing these patterns clearly with simple data analysis. The study does not aim to develop complex or predictive models but rather to observe and describe how visitor activity changes over time. This turns basic observations into measurable information and offers a simple tool for heritage sites to monitor visitor activity, even when resources are limited. The identified patterns also offer deeper insights into when and how visitor activity rises or falls. They reveal the direction of visitors' flow, not only its level. Some small differences also appear within the weekly trend. For example, weekday intensity drops in the afternoon, but some people stay late near closing time. At Beylerbeyi Palace, this pattern likely reflects the habits of residents rather than those of tourists. Regular work and leisure routines appear to influence visitation more strongly than seasonal travel patterns. Such insights can support site managers in organising schedules, maintenance, and visitor routing more efficiently.

Overall, this study highlights how big data sources are useful tools for monitoring tourist sites like previous studies in the literature (Shi et al., 2021; Reif and Schmucker, 2020). However, the study further introduces an entry point for simplified approaches by using semi-structured big data to monitor visitor patterns, especially in heritage sites, in a practical and easily applicable way.

5.1. Theoretical and Practical Implications

This study represents a preliminary investigation adopting a simplified approach to semi-structured big data to monitor and classify visitor flow patterns in heritage sites. As an initial step, it provides an empirical basis for developing more comprehensive monitoring frameworks in future research. This study also contributes to the literature on visitor monitoring and big data approaches. (Fuchs et al., 2025; Vongvanich et al., 2023; Mahdi et al., 2023; Milea et al., 2022; Castiglione et al., 2024; Barrena-Herran et al., 2025; Santiago-Iglesias et al., 2023; Shi et al., 2021; Reif and Schmucker, 2020). It demonstrates how a simplified exploratory approach can enhance the interpretability of big data in touristic sites.

The GPT data used in this study serve only as an example. Similar analyses can also be conducted using openly available or easily accessible big data sources from other platforms or semi-structured datasets. Previous studies often focused on complex models and prediction. Instead, this study shows the value of simple descriptive analysis for understanding visitor patterns.

This study is practice oriented. It aims to bridge the gap between data science and practical applications in tourism and heritage site management. From a managerial perspective, identifying weekly visitor patterns helps managers better control visitor flow, plan maintenance, allocate staff, and organise marketing activities and segmentation. This approach can also be applied in museums, archaeological sites, restaurants, cafes, and open-air museums where traditional counting systems are limited. Beyond analysis, the study provides operational value by enabling managers to monitor visitor patterns. These patterns can provide insights; for example, the difference between W1 and W2 can support staff planning and maintenance scheduling. Identifying the morning low-intensity period (H1) may also help redistribute demand, and the slope patterns (S1 and S2) can guide daily flow management. Taken together, these results illustrate that the simplified approach presented in this study allows weekly visitor patterns to be monitored using semi-structured big data and has the potential to be translated into meaningful visitor management implications.

5.2. Limitations and Future Recommendations

This study has some limitations. It only covers one heritage site and five observations of weekly data. Because of this, identified visitor patterns cannot be generalised for other seasons or other similar heritage sites. The Google Popular Times data show relative intensity, not exact visitor numbers. This means that the changes reflect visitor habits, not total counts. In addition, Google does not clearly share how the semi-structured data are processed, which is also a limitation.

While the analysis is limited to a single site and five weekly observations, it establishes an empirical foundation for further research. Future studies can analyse more sites in longer time periods. They can also use semi-structured data retrieved from other maps or mobile companies. Future studies could expand this approach by analysing seasonal changes or integrating different datasets. This micro-level practical analysis can also be applied on a macro scale at the destination level, where differences between visitor patterns across multiple sites can be compared. Other influential data, such as weather conditions and transportation modes, could have been used to strengthen the analysis. In addition, algorithmic or AI-based models can be used to identify visitor patterns and make predictions. Since there are only a few related studies in the literature, this topic is still open for further research and improvement.

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