Analysis of visitors' mobility patterns through random walk in the Louvre Museum

Yuji Yoshimura[a,b], Roberta Sinatra[c,d,e], Anne Krebs[f], Carlo Ratti[a]

[a] SENSEable City Laboratory, Massachusetts Institute of Technology, 77 Massachusetts Avenue, Cambridge, MA 02139, USA;

[b] Research Center for Advanced Science and Technology, The University of Tokyo, 4-6-1 Komaba, Meguro-ku, Tokyo 153-8904, Japan;

[c] NEtwoRks, Data, and Society (NERDS), IT University of Copenhagen, Rued Langgaards Vei 7, 2300 Copenhagen, Denmark;

[d] ISI Foundation, Torino, Italy;

[e] Complexity Science Hub, Josefstaedter Strasse 39, 1080 Vienna, Austria;

[f] Dominique-Vivant Denon Research Centre, musée du Louvre, 75058, Paris, Cedex 01, France;

email: yyoshi@mit.edu, rsin@itu.dk, anne.krebs@louvre.fr, ratti@mit.edu

Abstract. This paper examines visitors' sequential movements and their patterns in a large-scale art museum. Visitors' available time makes their visiting styles different, resulting in dissimilarity in the order and number of visited places and in path sequence length. Since the probability of the appearance of short combinations of nodes is higher than that of long combinations of nodes, shorter path sequences tend to appear more frequently than longer path sequences. This prevents us from evaluating the strength of visitors' mobility patterns, independent of their path sequence length. In order to solve this problem, we propose the random walk simulation model and compare the results with observed data. A random walk is a minimalistic model providing a reference line for the frequency of sequences as induced by the graph structure of the museum. The random walk simulations can therefore provide us with the probability of transitions between nodes and hence with the probability of each path of a given length. Thus, it enables us to compare the frequency of different path sequence lengths in the same framework. Our results indicate that short-stay visitors exhibit stronger patterns than long-stay visitors, confirming that short-stay visitors are more selective than long-stay visitors in terms of their visiting style. This is suggestive of the informal learning settings in which visitors shape their experiences through exploration in space.

Keywords: visitor studies; museum; random walk model; curatorial intent; architectural intent

1. Introduction

This paper analyzes visitors' sequential movements in a large-scale art museum, taking into account the spatial structure of the museum and the layout of exhibits dispersed over the space. The question asked is whether visitors' movements on a global scale (i.e., from their entrance to exit) become more random when more spatial and temporal choices are offered to visitors. This is significant for museum studies because the way visitors explore a museum shapes their experience and knowledge gained. We try to answer this question by using a random walk simulation model applied to the topological network structure of the museum and by comparing the movements in the model with those observed in a dataset acquired by Bluetooth sensors.

The analysis of visitors' movement and navigation through museums or exhibitions is considered one of the most important topics in museum studies (Melton 1935; Klein 1993; Bitgood and Hooper-Greenhill 1994; Falk and Dierking 2000; Hillier and Tzortzi 2006; Bitgood 2006; Wineman and Peponis 2009; Yoshimura et al. 2012, 2014, 2017b; Tzortzi 2014, 2015, 2017). Curators and exhibition designers are interested in how visitors approach and interact with exhibits during their visit, because the sequence of movements and the length of stay at each exhibit are factors that structure visitors' experience and shape their knowledge gained during their visits. The intent of curators is expressed through the layout and spatial hierarchies of the exhibits, as well as by the exhibits themselves (Tzortzi 2015). However, the museological arrangement of objects is not the only factor that frames visitors' experience. The spatial structure of the museum's layout plays an important role in controlling visitors' perceptions, drawing their attention to exhibits and consequently inducing their active engagement with the exhibits. The spatial structure provides movement choices for visitors, framing what they see and in which order. In addition, the architectural layout influences probabilistic encounters among visitors and their copresence in space (Choi 1999). Thus, the social aspect of museum visits has a strong impact on forming visitors' experiences in a museum (Choi, 1999; Hillier, 1996; Hillier & Hanson, 1984; Hillier & Tzortzi, 2006; Peponis et al., 2004; Tzortzi, 2014).

Nevertheless, the museum literature tends to overlook architectural intent (Hillier and Tzortzi 2006; Schorch 2013; Tzortzi 2015) and is therefore likely not to focus on the role of spatial features in forming visitors' experiences. In addition, researching visitors' movements and behaviors on a global scale is rarely conducted by either curatorial or architectural practitioners. Most previous studies were done in spatially limited galleries (e.g., Serrell, 1998) or in small- to medium-scale museums (e.g., Tzortzi, 2015). Furthermore, although in these studies the collected samples contain detailed behavioral descriptions (e.g., the number of stops, viewing time for each exhibit), the sample size is rather small. This shortcoming largely derives from the employed data collection methodology, which usually relies on a paper-and-pencil method of "timing and tracking" (Yalowitz and Bronnenkant 2009).

Table 1. Data collection techniques for studying visitors' paths in the context of museums

	Data capture	Obtained data	Total display area	Sample number	Result
(Melton 1935)	Observations	The time spent looking at each painting, the number of stops by visitors, and the total time in a gallery. He systematically increases the number of paintings in a gallery.	54.4 m^2	3,879	The number of stops in a gallery has a negative correlation with the total number of paintings, but the average viewing time for a painting remains constant (see Bitgood, McKerchar, & Dukes, 2013 for a summary)

(Serrell 1998)	Observations	The length of stay in the exhibition, the number of stops at the exhibits	Not available	8,507 from 110 exhibitions (max: 458)	The average length of stay divided by the exhibition's square footage (SRI), visitors who stop at more than half the exhibits (DVI)
(Bourdeau and Chebat 2001)	Observations and questionnaire	Visitors' movements, sketches of the pathways made by each visitor as reminiscences	Not available	60	The influence of the design of display on visitor flow
(Tzortzi 2015)	Observations	Paths through a gallery, the length of stay in each room, the time spent looking at each exhibit, number of stops by visitors	3,867 m^2 (average for 9 museums/ galleries)	42 (average number of visitors tracked in 9 museums/ galleries)	The viewing time of exhibits and the number of stops in front of them during visits
(Kanda et al. 2007)	RFID	Sequential movement between sensors, and the length of stay around the sensors	3,528 m^2	5,102	Typical spatial use and visiting pattern, spatial division by usage of visitors
(Tschacher et al. 2012)	Wearable gloves and questionnaire, tag with ultrawide band signals of 6-8 GHz	Locomotion, heart rate, and skin conductance, visitors' paths with a precision of 15cm	380 m^2	532	The relationship between physiological responses and aesthetic-emotional experiences of the exhibits
(Martella, et al., 2017)	Inexpensive radio-based proximity sensors	Time spent in front of an art piece, path sequence between artworks with the length of stay in the museum.	2,500 m^2	182	Heatmap of visitors' time spent in the museum, visiting types considering the path and distribution of visiting times analyzed by a clustering approach
(Yoshimura et al. 2014)	Bluetooth sensor	Sequential movements between exhibits where sensors were installed, length of stay in the museum	60,700 m^2	24,452	Spatial usage and visitors' behaviors based on their trajectories and length of stay

Table 1 shows an example of the data collection techniques for obtaining the paths of visitors in a museum, the sample sizes of the data, and the results of the analyses using these datasets. Although the recent ubiquity of digital technologies has revolutionized the way of collecting behavioral datasets in museums (Mygind and Bentsen 2017), there is a tradeoff between the sample size, types of data, and the dimension of the study area. For example, Tzortzi (2015) tracked visitors' behaviors in 9 museums or galleries, including the viewing time of exhibits and the number of stops in front of them. However, the maximum total display area and the largest sample size remain small (7,363 square meters and 100 visitors per museum, respectively). Hillier et al. 1996 tracked the first ten minutes of movement for 100 visitors entering a large-scale museum (the Tate Gallery in London, UK) instead of tracking their global movements. Their choice of methodology confirms the difficulty of tracking visitors' complete movements in a large-scale museum. Conversely, (Yoshimura et al., 2014; Yoshimura et al., 2012) successfully tracked more than 24,000 visitors on a global scale in a large-scale museum (i.e., around 60,000 square meters), but their collected sample does not contain the number of stops and the exact viewing times for each exhibit. Rather, they estimate the viewing time of an exhibit from a visitor's presence and its density around the exhibit (Yoshimura et al., 2017).

This paper proposes alternative approaches for the abovementioned methodologies. We simulate visitors' sequential movements in a global network of the museum by a random walk and compare the results obtained with the observed dataset. The random walk model is a probabilistic model that is well established in other fields but that has rarely been applied to museum studies. This model enables us to measure the strength of visitors' mobility patterns and evaluate them together with the observed dataset. Thus, the contribution of this paper is the application of the mathematical model for visitors' behaviors in a large-scale art museum and the interpretation of the results in the context of museum studies.

2. Methodology

This section describes the analytical framework applied in this paper.

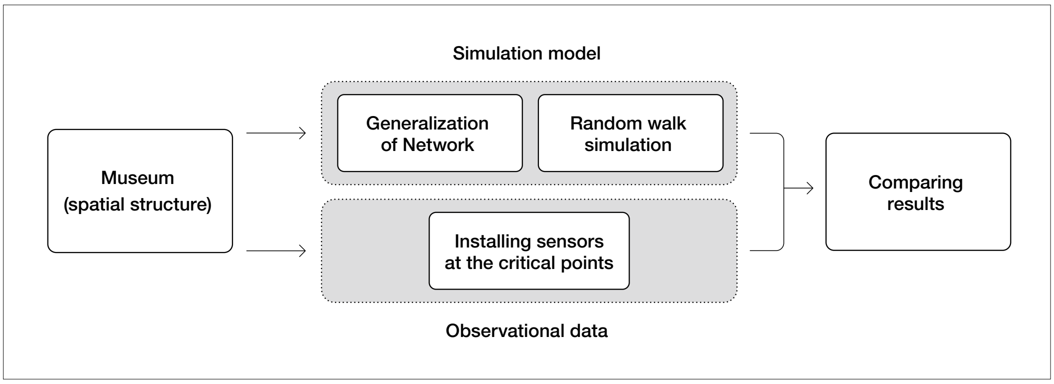
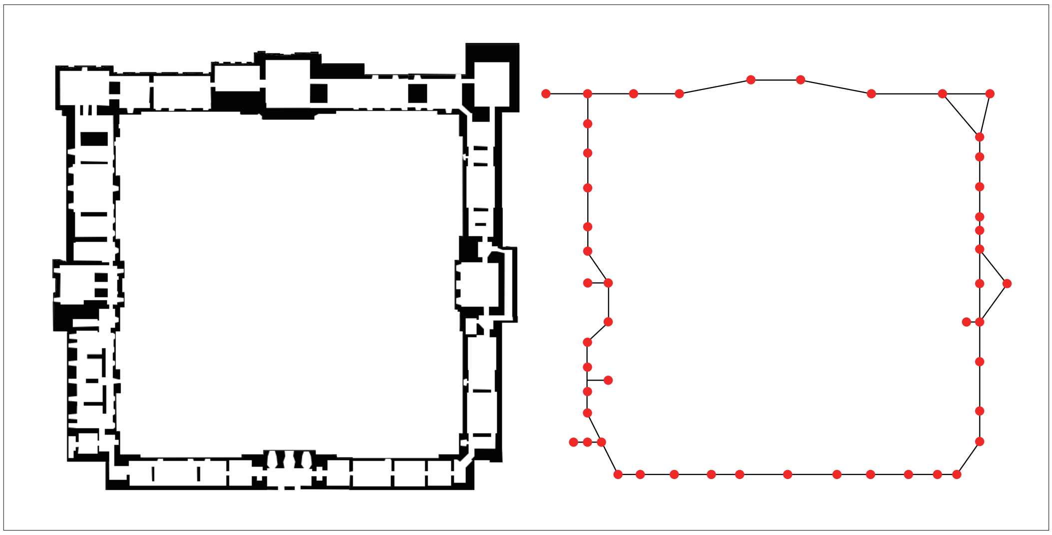


Figure 1. The flowchart of the analytical methodology.

Figure 1 presents the flowchart of our methodology. Our methodology is based on a network representation of the spatial layout, which enables us to handle the spatial structure of a museum as a topological relationship between rooms. We have two different data sources: one is the random walk model to simulate the visitors' sequential movements in such a network (see section 2.2), the other is the observational datasets derived from Bluetooth sensors deployed in the museum (see section 2.3). Finally, we compare those obtained results in order to measure the strength of patterns, observed from visitors' actual behaviors.

2.1. Generalization of the network

The first step in our analysis is to prepare the relevant network based on the spatial structure of the museum. Our case study is the Louvre Museum, Paris, which is one of the largest art museums in terms of exhibition area, the number of exhibits, and the number of visitors per year. Although the size of each room greatly varies, we identify a room as a node and a corridor or any other kind of connection between rooms as an edge.



(a) **(b)**

Figure 2. (a) The plan of the museum. (b) The primal representation of the museum, showing the route choices and sequences.

Figure 2 (a), (b) shows the diagram of the topological network as generalized from the building map. Figure 2 (a) presents the building map of the museum, and Figure 2 (b) represents the generated network, which is the topological representation of the spatial structure. A red point represents a room, and a line between points is a connection, along which visitors can move physically. We use this network for the following analysis.

2.2. Random walk

This paper applies the random walk model in the network of the museum and interprets the results in the context of museum studies. The random walk model is one of the simplest and most basic probabilistic models, and its properties and applications are well studied in different disciplines. The basic idea of the model is that the next location of a random walker appears randomly. For example, consider a game in which a fair coin is flipped and in which a move to the right is made when it is heads up and a move to the left otherwise. So, the walker, in this simple one-dimensional case, either jumps to the right with probability p or to the left with probability $q = 1 - p$ (in the case of a fair coin, $p = q = ½$). It can be shown that the probability of being at position m after N steps is given by a *binominal distribution*:

$$p(m, N) = \frac{N!}{\left(\frac{N+m}{2}\right)!\left(\frac{N-m}{2}\right)!}\, p^{\frac{1}{2}(N+m)} q^{\frac{1}{2}(N-m)} \tag{1}$$

or, called $n = \frac{N+m}{2}$ the number of steps in the increasing direction of the x axis,

$$p(n, N) = p_N(n) = \binom{N}{n} p^n q^{N-n} \tag{2}$$

Moreover, it can be proved that for unlimited time of playing the game i.e., $N \to \infty$, $Np \to \infty$ the probability converges to a normal distribution.

$$p(n, N) \rightarrow \frac{2}{\sqrt{2\pi\sigma_m^2}} e^{-\frac{1}{2}\frac{(\delta m)^2}{\sigma_m^2}} \quad (3)$$

where σ_m^2 = 4*Npq* and δm is a disturbance defined in such a way that:

$$\langle m \rangle = N(p\text{-}q) \Rightarrow m = \langle m \rangle + \delta m = N(p\text{-}q) + \delta m \quad (4)$$

and then

$$\frac{N+m}{2} = Np + \frac{\delta m}{2}; \frac{N-m}{2} = Nq - \frac{\delta m}{2} \quad (5)$$

The motion rule of the one-dimensional random walk can be easily extended to the case the walkers moves on a graph. Let *G* be a connected graph with *N* nodes and *L* edges. We start at a node v_0. If at a certain time step *t* our walker is on the node v_t, it moves on a neighbor of v_t with probability $\frac{1}{k_{v_t}}$, where k_{v_t} is the sum of the connections pointing out from the node v_t. We denote by II = $(p_{ij})_{i,j \in V}$ the matrix of transition probability of the random walk, namely:

$$\mathrm{II}_{ij} = \frac{1}{k_i} \text{ if } i\,j \in E, \text{ 0 otherwise} \quad (6)$$

The probability that a walker is a node *i* at time *t*, $p_i(t)$, is given by:

$$p_j(t+1) = \sum_i II_{ij}\, p_i(t) \quad (7)$$

Equation (7) can be expressed in vectoral form as:

$$P_{t+1} = II^T\, P_t \Rightarrow P_t = (II^T)^t\, P_0 \quad (8)$$

where P_t is a vector whose generic entry *i* is the node occupation probability at time *t*, $p_i(t)$. It can be proven that under certain conditions about the structure of *G*, for large *t* the node occupation probability does not depend on the initial distribution of walkers on the nodes.

2.3 Dataset for comparison

We compare the results obtained from the random walk simulation with the empirical dataset of the visitors' sequential movements. The dataset used in our study is the one employed in previous studies with Bluetooth sensors (Yoshimura et al. 2012, 2014, 2017b). The significant difference is that while previous studies used the dataset to uncover visitors' behaviors, we used it as the ground truth to be compared with the results from the simulation model. This is because the main objective of our paper is to demonstrate the analytical framework by combining the simulation model and the observed dataset. The museum network and the locations of key artworks used for the computation of the random walk model are the same as were used when the dataset was collected. Thus, it validates the usefulness of the dataset as the ground truth for the comparison with the simulation results.

Bluetooth detection is based on systematic observations that discover Bluetooth-activated mobile devices, making use of visitors' digital footprints or "data exhaust" (Mayer-Schönberger and Cukier 2013). The technique has been used to collect pedestrians' sequential movements outdoors (Paulos and Goodman 2004; Eagle and Pentland 2005; Kostakos et al. 2010; Versichele et al. 2012; Yoshimura et al. 2017a) as well as indoors (Delafontaine et al. 2012; Yoshimura et al. 2014, 2017b). The detection system works as follows: when Bluetooth-activated mobile devices enter a sensor's detection range, the sensor keeps detecting their presence until they exit. As the media access control (MAC) address of each mobile device is in most cases unique, the sensor network can identify the check-in and check-out of each mobile device with a timestamp. For the previous researches, the hash algorithm (Stallings 2001) was applied to maintain the anonymity of the visitors' data by converting the MACID into a unique identifier (Sanfeliu et al. 2010). In addition, we changed the visitor's unique ID each day. All of these processes make it almost impossible to identify an individual.

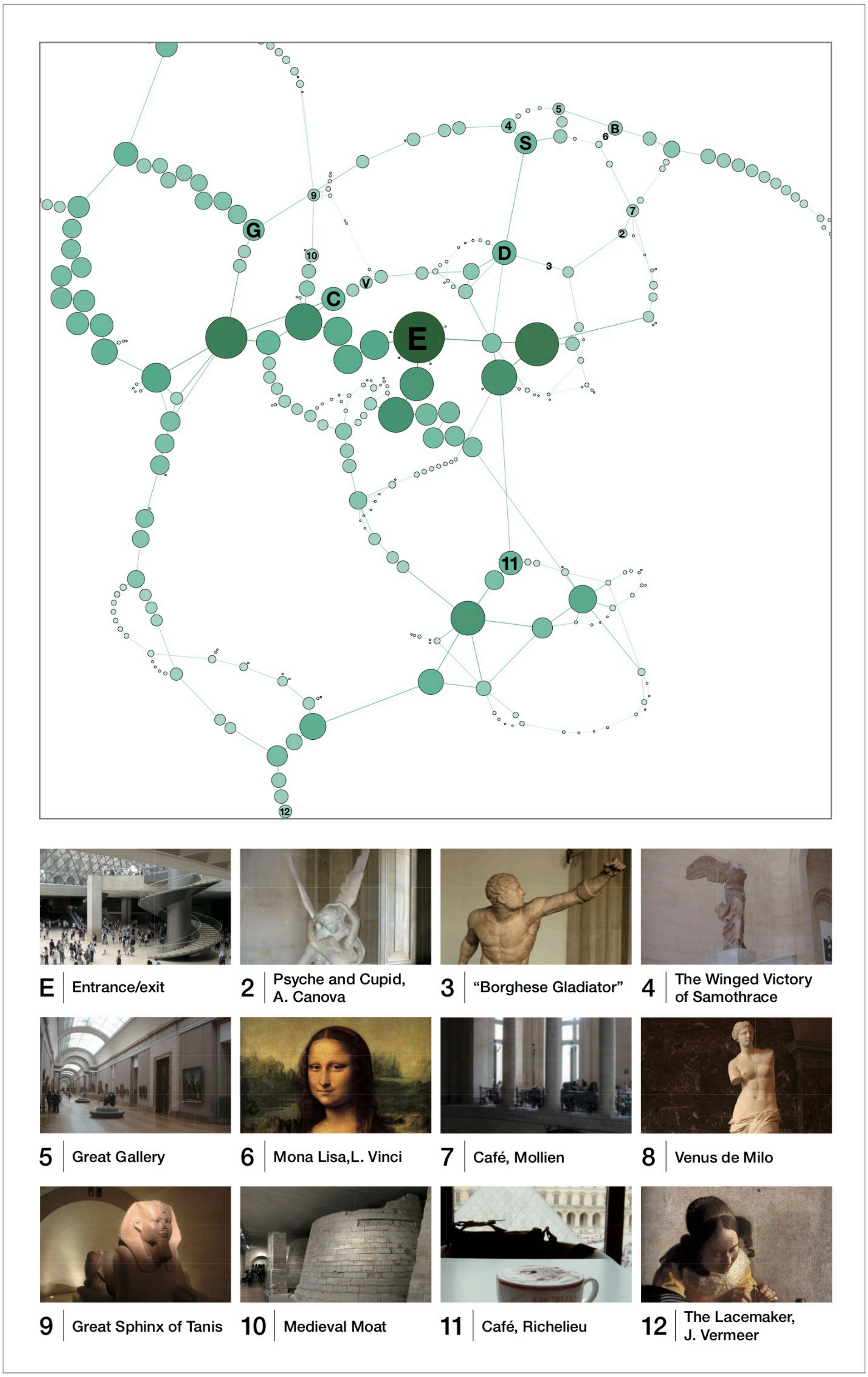


Figure 3. The topological representation of the spatial structure of the Louvre Museum. Each node corresponds to a room in the museum, and a link between two nodes corresponds to a corridor or another kind of connection between rooms. The nodes marked by letters correspond to rooms where sensors are located. The nodes marked by numbers indicate popular artworks near each sensor.

Figure 3 presents the topological representation of the spatial structure of the Louvre Museum, with the location of sensors shown by letters: Hall (E), Gallery Daru (D), Venus de Milo (V), Salle des Caryatides (C), Great Gallery (B), Victory of Samothrace (S), and Salle des Verres (G). The data collection was performed in 24 days during three different audits: from 30 April to 9 May 2010, from 30 June to 8 July 2010, and from 7 August to 18 August 2010.

2.4 Deriving sequential movements from the raw dataset

The raw dataset collected by the Bluetooth sensors consists of the unique ID of each mobile device and the timestamp of registration assigned by each sensor when the mobile device enters the detectable area and exits from it. Subtraction of the exiting timestamp from the entering one gives the length of stay at each location. Examining the first timestamp in sensor E (the entrance) and the last one in sensor E (the exit space) indicates the length of stay in the museum.

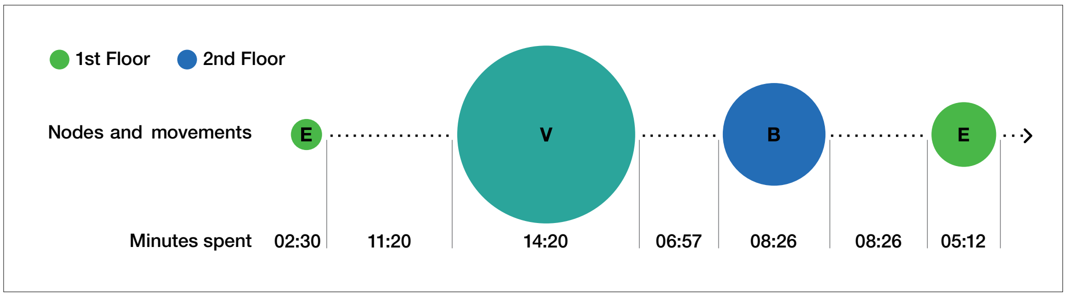


Figure 4. The visualization of the concept of visitors' visit to the node and their length of stay at the node.

Figure 4 shows the example of the visualization for the visited nodes and their length of stay in each node by a visitor. For example, the visitor visited node E and stayed there for 02:30 min. Then, the visitor visited node V, staying there for 14:20 min. and took 06:57 min. for transiting from the previous node to the subsequent node, and so on.

Table 2. Example of the dataset

Rffr	Date	Path	Check-in	checkout	Stay length
Unique ID	2010-04-30	E-V-B-E	10:05:30	12:10:42	02:05:12

Based on this information, we create sequential notations, shown in Table 2. The process is as follows: first, we extract all data registered by each sensor and sort them by timestamp; second, we extract the location label assigned to each sensor from the above-mentioned sorted dataset. We disregard the length of stay at each location. As an example of this processing, E-S-E indicates that a visitor enters the museum through sensor E, moves to sensor S, and then exits the museum via sensor E. For the analysis in this paper, we selected the sequences that started and finished at node E, which is the entrance and exit of the museum. After data cleanup and processing to remove inconsistencies, 24,452 unique devices were identified and used in our analysis.

2.5 Short- and long-stay visitors

Our previous research focused on extracting the factors that determine the visitors' length of stay in the museum (Yoshimura et al. 2014). For this purpose, we split our sample into deciles based on the duration of stay, effectively obtaining 10 equally sized clusters of ~2446 visits each. We defined the first bin as short-stay visitors and the last one as long-stay visitors.

2.6 Spearman's correlation

To clarify the distribution of each path, we look for a correlation between the duration of a visitor's stay in the museum and his or her chosen trajectory. We calculate the number of visitors using every possible trajectory across the museum that is present in each of the aforementioned partitions. Then, for every different path, we calculate the correlation between the partition order and the number of visitors in that partition. Since we know that the partitions increase monotonically with the duration of stay, if a correlation exists, it can tell us which trajectories are more frequent when a visitor stays for different lengths of time. We quantify the correlation by means of Spearman's correlation coefficient (Corder and Foreman 2009), denoted by the symbol ρ, and a p-value. Spearman's correlation coefficient is used to assess how well the relationship between two variables (x, y) can be described by a monotonic function, where the derivative of y with respect to x is greater than zero, $\frac{dy}{dx} > 0$ (see Appendix).

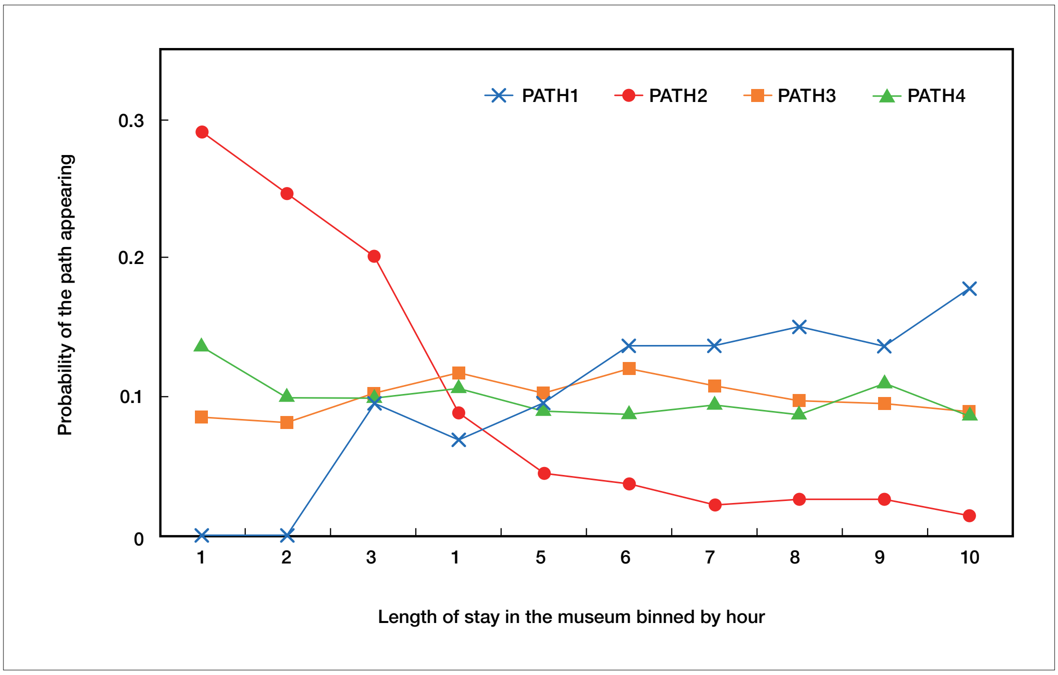


Figure 5. Length of stay vs frequency of appearance for four different types of paths normalized by the total number of appearances of each path

Table 3. Path sequence, Spearman's correlation coefficient, p-value, middev

Path	ρ	p	middev
PATH1 (E-D-S-B-S-D-V-E)	0.93%	5.38E-05	0.53%
PATH2 (E-S-D-V-C-E)	0.96%	1.02E-05	-3.03%
PATH3 (E-S-E)	-0.12%	0.7328	0.53%
PATH4 (E-D-S-B-E)	-0.56%	0.0957	-1.96%

See Figure 5 for an example of the procedure we used. All the paths in our datasets can be classified into four types according to the frequencies across the 10 partitions. We can see that the frequency of PATH1 increases as the length of stay increases. Conversely, the frequency of PATH2 decreases as the length of stay increases. According to Spearman's correlation coefficient, PATH1 has a significant positive correlation with the partition order (ρ=0.93, p=5.83E-05), while PATH2 shows a significant negative correlation (ρ=-0.96, p=1.02E-05). This would imply that visitors tend to use PATH1 more often when they stay longer in the museum, thus making PATH1 characteristic of long-stay visitors, while PATH2 is chosen more frequently by short-stay visitors. Figure 5 also shows that PATH3 and PATH4 are more evenly distributed across partitions, suggesting that there is no clear tendency to choose any of these paths depending on a visitor's length of stay in the museum.

In addition to this, if we focus on the first partition (equivalent to the short-stay visitors) and the last partition (long-stay visitors), we find trajectories that appear in one of these two partitions but not in both, effectively finding frequent paths that are exclusive to either group. We also quantify correlations of the mean of the p-values for every distinct path in our dataset and their frequencies throughout the dataset.

3. Results

This section presents the results of our analysis. First, we examine the paths obtained from the random walk simulation in terms of path sequence length, as not all paths are valid for the subsequent analysis. Second, we perform the statistical analysis for the distribution of path types for short- and long-stay visitors. Finally, we compare the results obtained with the observational data from the Bluetooth sensors. For this purpose, we introduce an R-value, which is a ratio between the simulation data and the observational data.

3.1 Validity of the path length

The path followed by a visitor through a museum can be represented as a sequence of letters, each corresponding to one of the unique locations of the museum. The sequences in the present study are composed of seven letters, i.e., the number of sensors installed in the museum, and start and end with the letter E, which corresponds to the entrance/exit of the museum. Each sequence is at least three letters long, as we consider only visitors who were detected in the proximity of at least one sensor besides the one at the entrance/exit. So, for example, the shortest sequence we observe is of the kind E-S-E. In theory, there is no upper bound to the maximum length of a sequence, since a person can visit a location more than once. In our study, however, the longest sequence observed consisted of 30 letters.

In general, if we have *N* nodes (in our case, 7, the number of sensors installed in the museum), we can form *N^i* different sequences of length *i*. In our case, *i* can range from 3, the shortest sequence possible, to 30, the longest sequence observed. So, all possible sequences with a length between these two extremes sum up to

$$\sum_{\mathrm{i}=3}^{x} N^{x} = \frac{N^{x+1} - N^{3}}{N-1} \tag{9}$$

where x = 30, or the maximum length considered (Sinatra et al. 2010). However, not all the possible sequences are valid for the analysis because there are not enough data to validate long paths (Sinatra et al. 2010). That is, for high values of x, we do not have enough paths of length x in our observed data to assess the statistical significance of the path. The maximum length S of the path that is valid for the analysis can be calculated based on the number of nodes N and the sample size of paths (24,452 in our dataset). As we consider only paths starting at the entrance (E) and finishing at the exit (E), we calculate the maximum path length for our analysis by subtracting the fixed first and last nodes; hence, we use S-2. In addition, we make sure that the same node is not repeated consecutively. Therefore, the number of possible nodes that can be selected at each step of the visits is N-2 (excluding E and the letter of the currently visited node). Taken together, we need to solve the following inequality to determine S:

$$(N-2)^{S-2} < 24{,}452 \qquad (10)$$

which gives $S = 8$, meaning that we cannot analyze paths longer than 8.

Moreover, shorter path sequences (e.g., E-S-E) tend to appear more frequently than longer path sequences (e.g., E-D-S-B-D-V-E). Because the probability of the appearance of short combinations of nodes is higher than that of long combinations of nodes, we cannot compare the frequencies of paths of different lengths.

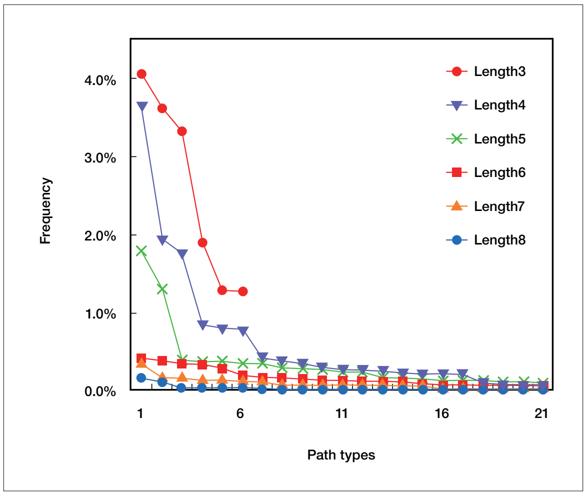


Figure 6. Top 20 of ranking of the random walk frequency in case of the longer stay-type visitors with path length less than 7, which is valid for the analysis

Table 4. Top three paths appearing by random walk for longer and shorter stay-type visitors and the respective distributions for each.

Path	Percentage	Path	Percentage
Longer Stay Type Visitors		*Shorter Stay Type Visitors*	
Path length 3			
E-D-E	4.06%	E-D-E	6.86%
E-S-E	3.63%	E-C-E	5.25%
E-C-E	3.33%	E-S-E	4.56%
Path length 4			
E-D-S-E	3.67%	E-D-S-E	4.64%

E-V-C-E	1.95%	E-V-C-E	3.35%
E-S-B-E	1.78%	E-S-B-E	3.11%
Path length 5			
E-D-S-B-E	1.80%	E-D-S-B-E	3.17%
E-D-V-C-E	1.31%	E-D-V-C-E	3.15%
E-S-V-C-E	0.42%	E-S-B-D-E	0.96%
Path length 6			
E-D-S-V-C-E	0.42%	E-D-S-B-D-E	0.98%
E-D-S-B-D-E	0.40%	E-S-B-D-S-E	0.65%
E-D-S-D-S-E	0.36%	E-D-S-V-C-E	0.55%
Path length 7			
E-D-S-B-D-S-E	0.36%	E-D-S-B-D-S-E	0.66%
E-D-S-D-S-B-E	0.18%	E-S-B-D-S-B-E	0.44%
E-S-B-D-S-B-E	0.17%	E-S-B-D-V-C-E	0.44%

Table 4 shows the result of the random walk frequency applied to seven nodes. The *x*-axis in Figure 6 takes the rank of the frequently appearing path types at each path length, ordered by the number of occurrences. As we can observe, the frequency of each rank in each path length decreases as the path length increases. As mentioned earlier, this reveals the effect that shorter path lengths appear more frequently than longer path lengths, preventing us from comparing all extracted paths under the same conditions.

Although a visitor's choice of movements in a museum likely depends on the past locations visited as well as the visitor's prior knowledge of the museum (e.g., repeaters or first-time visitors), a random walk is a minimalistic model providing a reference line for the frequency of sequences as induced by the graph structure of the museum. The random walk simulations can therefore provide us with the probability of transitions between nodes and hence with the probability of each path of a given length.

3.2. Patterns of visitors' sequential movements

This section analyzes the relationship between the distribution of visitors' path types and their frequencies. We extract all path types that appeared in each group and count the number of appearances of each path, resulting in the frequency of each path. As a result, 1,312 different path types are subject to further analysis for the long-stay visitors, and 373 for the short-stay visitors. In a similar way, we examine the random walker dataset: 833 paths for the long-stay random walkers and 518 paths for the short-stay random walkers.

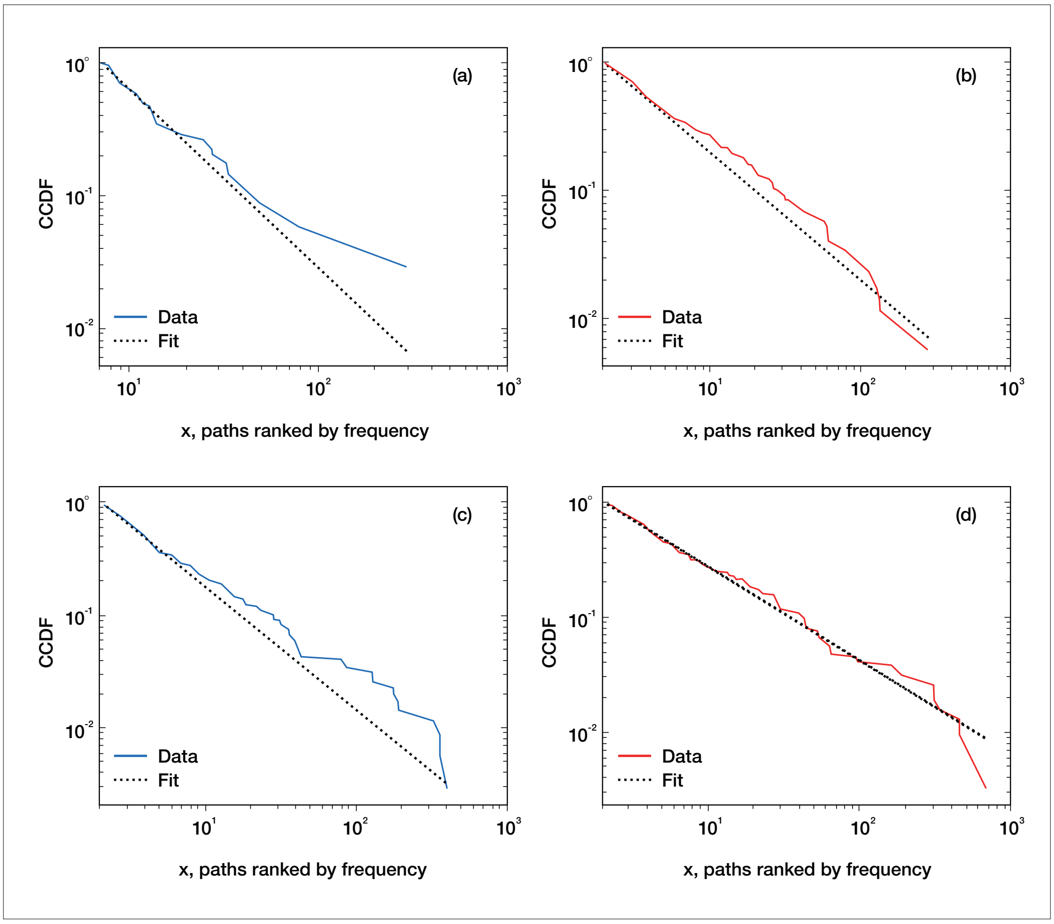


Figure 7. Complementary cumulative distribution function (CCDF) of visitors' path types and their frequencies from (a) the long-stay visitors, (b) the short-stay visitors, (c) the long-stay random walkers, and (d) the short stay random walkers. The dashed lines in the log-log plots of all panels indicate that p (X > x) follows a power law, where the alpha parameter = 2.33, 1.99, 2.08, and 1.82 for (a), (b), (c), and (d), respectively.

Figure 7 presents the complementary cumulative distribution function (CCDF) of the frequencies of visitors' path types from (a) long-stay visitors, (b) short-stay visitors, (c) long-stay random walkers, and (d) short-stay random walkers. The black dashed line shows the CCDF of the power law probability density function:

$$P(x) \propto x^{-\alpha} \tag{11}$$

Our results show that the distribution of the path types for the short-stay visitors as well as random walkers (red lines) can be better approximated by power laws (with exponents α=1.99 and 1.82, respectively) than the long-stay visitors (blue lines, α=2.33 and 2.08, respectively). To test whether the power law is the best description for our dataset, we performed a comparative analysis of the goodness of fit of another possible candidate distribution for our datasets, the exponential function. We compared the power-law and exponential-function fits to our four individual datasets through the maximum-likelihood method as well as the log-likelihood ratio test provided by (Alstott et al. 2014). The results indicate that all datasets except the one for the long-stay visitors can be better fitted by power laws than by exponential functions (p-value < 0.01) and that the long- stay random walkers can be better fitted with a log-normal than with a power-law distribution (p-value = 0.02).

We can interpret these results as follows: many short-stay visitors tend to use the same paths from the entrance to the exit, so a few path types have a much higher frequency, while most path types appear only once. Conversely, also most of the long-stay visitors use a few path types, but their frequencies are not so high as those for the short-stay visitors. Rather, most of the long-stay visitors are likely to follow different trajectories. As a result, the shorter the visitors' lengths of stay become, the more the visitors follow a similar sequence through the museum.

3.4 Patterns of visitors' sequential movements by R-value

This section compares the simulated movements and the observed ones. Since the probability of a given path decreases as the path length increases, we cannot compare paths of different lengths with each other. For this reason, we compare the probability of each observed path length with the probability provided by the random walk model. We introduce the *R*-value, defined as the observed frequency of a path divided by the frequency of the same path in the random walk model, in order to measure the strength of each path and to identify patterns in the museum. That is, if *R* is large (>> 1), the corresponding path is a strong pattern, as it suggests that the observed path appears much more frequently than in the random walk model.

Table 5. Top five paths with the highest frequency, ordered by the observed paths in each group.

Path	Observed Path	Random Walk	R	ρ	p-value
Longer Stay Type Visitors					
E-S-E	0.216	0.0362	5.859	0.753	0.0117
E-D-S-B-E	0.058	0.0179	3.246	0.182	0.6140
E-D-S-B-D-V-C-E	0.028	0.0012	22.558	-0.863	0.0012
E-B-E	0.024	0.0129	1.898	0.109	0.7634
E-D-S-B-D-E	0.023	0.0039	6.012	-0.899	0.0003
Shorter Stay Type Visitors					
E-S-E	0.123	0.0455	2.703	0.753	0.0117
E-D-S-B-D-V-C-E	0.060	0.0045	13.392	-0.863	0.0012
E-D-S-B-E	0.056	0.0316	1.780	0.182	0.6140
E-D-S-B-D-E	0.050	0.0098	5.120	-0.899	0.0003
E-D-S-B-D-V-E	0.040	0.0023	17.349	-0.522	0.1210

Table 5 presents the top five paths with the highest frequency, ordered by the observed paths in each group. Within them, E-S-E appears with the highest frequency in both groups. In addition, we can observe that its frequency is higher among the long-stay visitors than among the short-stay visitors. More than 20% of the long-stay visitors visit only one node and explore other areas without passing through any other node. However, if we focus on the R-value, the path with the third-highest frequency, E-D-S-B-D-V-C-E, appears with the highest R-value among the paths of the long-stay visitors. This indicates that although the former path (i.e., E-S-E) has a higher frequency than the latter (i.e., E-D-S-B-D-V-C-E), the latter has a stronger pattern than the former. In a similar way, E-B-S-D-V-C-E has a much higher R-value than other paths among the short-stay visitors, although its frequency is lower ranked (eighth place).

Table 6. All paths that satisfy both the established thresholds (i.e., ρ>0.6%, p<0.01%).

Path	R	ρ	p	Frequency (rank)
Longer Stay Type Visitors				
E-D-S-B-S-D-E	21.16	0.88	0.0006	0.007 (18)
E-C-V-C-E	0.58	0.79	0.0062	0.002 (54)
Shorter Stay Type Visitors				
E-B-S-D-V-C-E	369.708	-0.87	0.0009	0.02 (8)
E-B-S-D-V-E	213.108	-0.79	0.0065	0.007 (28)
E-D-S-V-B-D-E	165.638	-0.88	0.0005	0.003 (48)
E-D-S-B-D-B-V-E	148.343	-0.77	0.0084	0.0008 (113)
E-V-D-S-D-B-E	89.680	-0.78	0.0069	0.003 (51)
E-C-V-D-S-B-E	71.176	-0.91	0.0002	0.027 (7)
E-V-C-D-S-D-E	67.285	-0.87	0.0008	0.006 (33)
E-C-V-D-S-E	45.376	-0.83	0.0024	0.025 (10)
E-V-C-G-D-S-E	22.365	-0.84	0.002	0.0013 (81)
E-C-G-D-S-E	14.276	-0.85	0.0014	0.0013 (82)
E-D-S-B-D-V-C-E	13.392	-0.86	0.0012	0.06 (2)
E-S-D-V-C-E	11.761	-0.96	1.02E-05	0.03 (6)
E-V-D-S-B-E	8.35	-0.92	0.0001	0.018 (12)
E-S-D-V-E	5.507	-0.81	0.0041	0.008 (26)
E-D-S-B-D-E	5.12	-0.89	0.0003	0.05 (4)
E-D-S-V-C-E	4.80	-0.76	0.0097	0.02 (9)
E-D-V-C-D-S-B-E	4.16	-0.79	0.0059	0.001 (69)
E-D-V-C-S-E	2.13	-0.80	0.0046	0.0008 (114)
E-D-S-D-E	0.74	-0.80	0.0052	0.0048 (38)

Table 6 presents all the paths that satisfy both above-mentioned thresholds (i.e., $\rho > 0.6$, $p < 0.01$). We sort them by R-value. Nineteen paths are extracted from the short-stay visitors, but only two paths are found in the long-stay visitors. Here again, a larger number of path types appears among the short-stay visitors than among the long-stay visitors. In addition, the R-value of the short-stay visitors is significantly larger than that of the long-stay visitors. For example, the highest R-value from the long-stay visitors is similar to the one ranked 10th in the short-stay visitors, and the second highest one (i.e., E-C-V-C-E) is lower than all R-values from the long-stay visitors. Actually, the highest R-value from the short-stay visitors (i.e., E-B-S-D-V-C-E) is 17 times larger than the highest R-value from the long-stay visitors (i.e., E-D-S-B-S-D-E).

All these facts indicate that the most frequently appearing pattern from the short- stay visitors is quite strong, and that of the long-stay visitors is relatively weak. This is probably because the short-stay visitors have a limited time available, so they might follow optimal paths to be able to visit the "must-see" art pieces in the most efficient way. As a result, the visiting style of the long-stay visitors shows higher diversity than that of the short-stay visitors. The strength of this selectivity gets weaker as the length of stay increases.

4. Discussion

This paper examines visitors' sequential movements and their patterns in a very large-scale art museum. We analyze how the length of stay in the museum influences visitors' visiting styles, taking into account the spatial structure of the museum and the layout of exhibits. Our findings enhance the knowledge of visitors' behaviors and help to assess curatorial intent and preventive conservation processes in terms of visitors' actual behaviors. In the following, we discuss the implications of our results in the context of Museum Studies, focusing on visitors' mobility patterns on local and global scales.

Figure 8. (a) The gallery Daru toward the *Winged Victory of Samothrace* and staircase. (b) The perspective to the *Winged Victory of Samothrace* from the bottom of the stairs from the gallery Daru. (c) The view from the room's landing. (d) The view from the exit of the Italian gallery. (e) The view from the exit of the Apollo gallery.

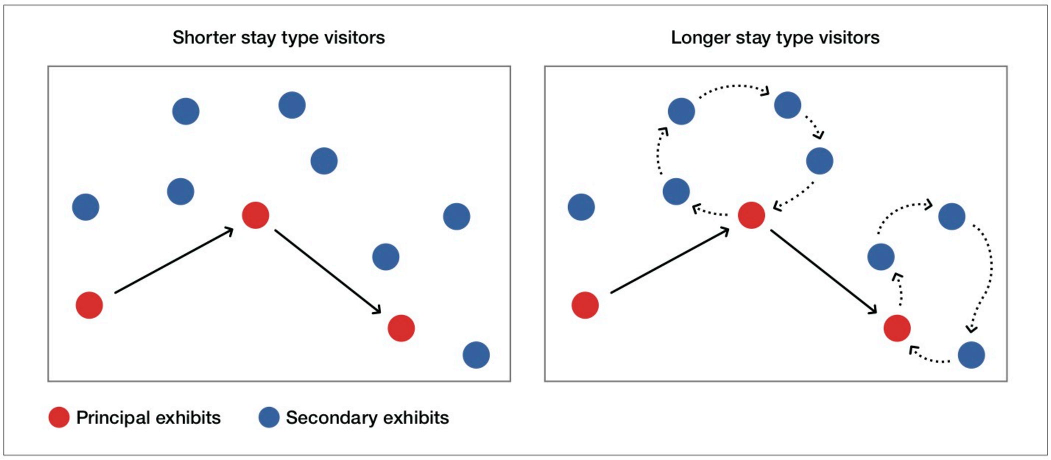
Figure 8 (a) – (e) shows the different views of the space environment of the *Winged Victory of Samothrace*. This exhibit is considered one of the most iconic artworks of the Louvre, together with the *Mona Lisa* and the *Venus de Milo*. Because, installed in 1883, the *Winged Victory of Samothrace* is placed in a striking position to present the Greek sculpture, in the grand stairway with the skylight from the top, a better spatial harmony between architectural and museological intent is achieved than with the *Mona Lisa* and the *Venus de Milo*. However, Newhouse (2005) argues that with the change of the Louvre's main entrance (i.e., the construction of Ieoh Ming Pei's glass pyramid), multiple routes are now provided for the visitors to choose from, thereby diminishing the dramatic encounter between the exhibit and the visitors. The previous spatial layout automatically led the visitors to the bottom of the grand stairway; thus, the curatorial strategy is largely achieved as a sequence: visitors arrive from the gallery Daru [see Figure 8 (a)], walk upstairs [see Figure 8 (b)], and encounter the exhibit [see Figure 8 (c)]. They are not expected to mainly approach the exhibit from either lateral side of the room [see Figure 8 (d) or (e)], as is the case in the current spatial layout. Our proposed methodology can quantify visitors' route choices and evaluate to what degree the curatorial intent would be achieved even with multiple route choices.

Our current analysis reveals that 71.1% of the visitors who come from the main entrance of the museum (node E) and the gallery Daru (node D) move to the *Winged Victory of*

Samothrace. This contrasts with the observation that only 5.6% of the visitors chose to move to the *Venus de Milo* when arriving in the location where they can make a choice (i.e., node D). Conversely, only 23% of the visitors chose the Richelieu entrance route or the Sully route, suggesting that they approach the *Winged Victory of Samothrace* from the lateral entrance. Considering that only 23 % of the visitors start their tour from either Richelieu or Sully entrances, the curatorial intent largely corresponds to the visitors' actual movements and their sequential patterns. It must be reminded that the Denon wing of the Louvre exhibits the *Mona Lisa* painting, which reinforces the attraction power of the wing, added to the specific attraction power of the *Winged Victory of Samothrace*.

For this space, the spatial layout was used to enhance the dramatic impact of the exhibits, and the spatial hierarchy corresponds to the hierarchy of the exhibits displayed. However, the exhibits are also used to dramatize the spatial impact; consequently, the architectural intent matches the curatorial intent in terms of grandeur, thereby improving the quality of visitors' aesthetic experience and filling everyone with wonderment in the space.

Let us now turn to the scale of the whole building, from the microscale of the space of a single exhibit. Regarding visitors' global behaviors, our findings reveal that short-stay visitors have a stronger pattern of movements than long-stay visitors. This could be considered as an unexpected result because we tend to assume that, theoretically, visitors are free to explore any room, having multiple movement choices due to the open-plan layout, which offers almost random sequences. Since the number of possible combinations of visitors' paths is enormous, many different path types are expected to appear. Thus, we expect the visitors' global mobility pattern to be random. However, our results show almost the opposite: the path types that appear are quite limited and standardized, with fixed sequences, despite a huge number of exhibits and many possible trails to select from. It therefore validates the major contributing factor of the attraction power of iconic artworks, particularly in the case of superstar museums (Frey 1998). This is probably not specific to the Louvre museum – even if exacerbated at the Louvre – and is particularly relevant for Museum Studies and practitioners. Such a finding may suggest that curators and mediators should consider organizing the intended messages and construct the hierarchy of those messages according to these open but limited and standardized patterns.



(a) **(b)**

Figure 9. (a) The diagram of the path of short-stay visitors. (b) The diagram of the path of long-stay visitors.

Figure 9 shows the concept of the paths for short-stay and long-stay visitors. Due to the limited time budgets available, the short-stay visitors could visit only "must-see" exhibits (main or renowned exhibits), skipping others in the local galleries, and transit to the next one right after seeing the previous one [see Figure 9 (a)]. Thus, they are almost forced to follow the most optimal path on a global scale. Consequently, the intended message along with the principal axis (on a global scale) would probably be received better, in terms of viewing order, by the short-stay visitors. Conversely, the long-stay visitors would have more time available, enabling them to visit not only the principal exhibits but also other collections (assumed to be lesser known or popular) in the local galleries. That is, the long-stay visitors have more flexibility in their behavioral choices. As a result, the messages organized in secondary exhibits would probably be better received by long-stay visitors than by short-stay visitors. The most optimal route provides the general direction and guides mainly the path for short-stay visitors, while the local connections from the axis of the main direction give flexibility, enabling long-stay visitors to explore the local spaces. Both types of visiting patterns may be correlated to other relevant variables: time spent in Paris; previous knowledge or lack of knowledge of the Louvre collections; size of the group of people visiting together; and of course, level of expertise in history or art history. Further research would benefit by exploring the role of these determinants and implementing complementary fieldwork including interviews and questionnaires.

The visitors' time budget differentiates their mobility patterns: bringing to light such differences would help to create a good curatorial policy, customizing it to the types of visitors' behaviors. The interplay between the global sequence and the local circulation pattern determines the visitors' paths. The global sequence can be the general guide for short-stay visitors, while the combination with the local circulation pattern is the key for exploring the behaviors of long-stay visitors. Thus, the main axis acts as a recurrent and space for choice, providing the orientation of the general movements and controlling access to the local galleries to facilitate local circulations. This strategy could redistribute visitors evenly among spaces and would consequently help to reduce hyper-congestion in a museum (Krebs et al., 2007). However, the collections' display is organized in order to present coherent grouping of artworks in scientific terms, thereby limiting new combinations or more innovative groupings.

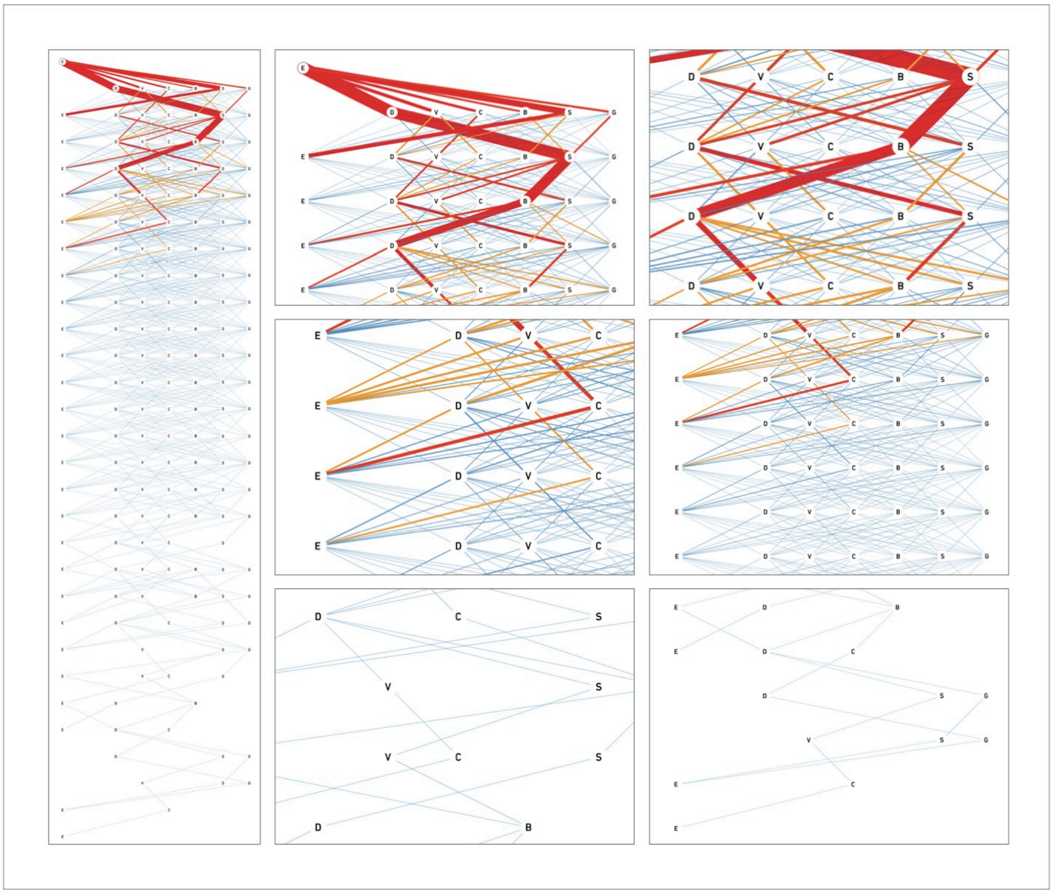


Figure 10. The most frequently appearing paths, which emerged in a bottom-up way

All these observations suggest that there exists an underlying pattern of visitors' sequential behavior beneath its heterogeneity, notwithstanding that "exhibition visitation is a highly individual activity" (Hein 1998) (page 105). Visitors may have similar tastes and habits, making their behaviors similar. The superimposition of the behaviors of many individuals makes patterns seem to be self-organizing or generated bottom-up from seemingly chaotic, disordered, and crowded movements (Musse and Thalmann 2011). We visualize these results in Figure 10, in which we trace the sequential movements of all visitors and identify the most frequent ones in a bottom-up way. The visiting behaviors in the Louvre consist of almost opposite behaviors with respect to scale: a global sequence along the main axis and local exploration on the neighborhood scale (i.e., galleries), but those opposite behaviors together result in the collective experience in the museum.

Our proposed method is valuable and provides novel perspectives for existing research, but it also has several limitations. Our analysis is based on a computer simulation model that is compared with large-scale datasets obtained by Bluetooth sensors. In contrast with manually acquired observations, interviews, or questionnaires, the current dataset does not contain any qualitative information about psychological factors or decision-making processes. Thus, our current analysis cannot examine these factors and processes for visitors' behaviors. Also, the influence of museum guides, orientation signs, and audio guides, as well as visitors' intentions, projects, and aspirations are not considered in this paper. All of these are probably involved in determining the paths of visitors and the lengths of stay at exhibits and need to be further explored if we want to avoid possible misinterpretations of the data. We put this as a limitation of our current analysis and make the case that a combination of methods would strongly benefit and enrich current research devoted to mobility patterns and Museums Studies at large.

5. Conclusion

Our proposed methodology provides us with more insight into visitors' mobility patterns in large-scale art museums and consequently helps to enhance our knowledge of visitors' behaviors. Previous museum studies have the shortcoming that they investigate visitors' behaviors on a global scale from museum entrance to exit, especially for large-scale art museums. These studies are likely to focus on either the macroscopic scale (i.e., the basic demographic composition of visitors) or the microscopic scale (i.e., visitors' behaviors in individual galleries), so there are hardly any studies on the mesoscopic scale (Yoshimura et al. 2014). This shortage largely derives from the data collection methodology employed, which relies on manually based timing and tracking (Yalowitz and Bronnenkant 2009). Although the introduction of emerging technologies has revolutionized the way of collecting relevant datasets (Mygind and Bentsen 2017), case studies for large-scale art museums are still limited. In addition, there is a lack of robust tools for analyzing large-scale datasets of museum visitors' behaviors. Our proposed methodology can fill these gaps.

Our results and findings are useful for constructing a narrative for both short-stay and long-stay visitors. However, creating secondary messages around non-principal exhibits is more effective and probably will be received better by long-stay visitors than by short-stay visitors. This may help to reduce congestion in museums because we could influence the paths of specific groups by creating subsequences. In addition, we can optimize the museum's facilities by considering visitors' routes and lengths of stay at each specific artwork as well as in the museum. Finally, our analysis and results provide significant information with which to create or improve interactive applications for mobile devices such as audio and visitor guides.

Appendix (or "Material and Methods")

Algorithm for sequences extraction. Let's define $S_i = \{s_{1i}, s_{2i} \ldots s_{pi} \ldots s_{Pi}\}$ the set of all the P possible sequences of length i, where $i = \{k, k+1, k+2 \ldots I\}$, where i is the length of the longest trajectory in the dataset, and k is the minimum meaningful trajectory in the dataset. Let's also define $f(s_{pi})$ as the number of visitors in the dataset that used the sequence s_{pi} during their visit to the museum. Finally, lets define T as a table containing the resulting patterns and their frequencies.

Given that N = {1,2…n}, the set of nodes in the museum, the high-level steps of the algorithm are as follow:

```
for i in k to I:
        for s_pi in S_i:
                if f(s_pi) > 0
                        save s_pi in T
                        save f(s_pi) in T
                        for n in Neighbors(s_pi[i]):
                                add s_pi+1^n to S_i+1
```

being that $s_{pi+1}{}^{n}$ is a sequence of length $i+1$ that results from adding a node n belonging to the neighbors of the last node of the sequence s_{pi} (i.e. s_{pi}.[i]), to the sequence s_{pi}.

This algorithm starts from the basis that any sequence including a subsequence cannot be present if such subsequence is not present in the dataset. It then iteratively finds all sequences of a minimum length k that are actually used by at least one visitor. Then builds all the possible sequences of length k+1 based on the existing sequences of length k and discarding the inexistent ones. By discarding the shortest-length sequences, the algorithm converges faster than if every possible sequence was tested.

We used $k = 3$ as a starting sequence length, based on the fact that the shortest possible trajectory, (e.g. 0-8-0 or 0-3-0) has a length of three. The resulting table T includes all sequences that appear in the dataset, along with their respective frequencies. Not every possible sequence is going to appear in T, since there are paths that are impossible for visitors to follow due to the physical distribution of the museum.

Spearman's correlation coefficient. The Spearman's correlation coefficient ρ (Corder & Foreman, 2009) is a non-parametric measure of statistical dependence between two variables. The coefficient evaluates how well the relationship between two variables (x, y) can be described by a monotonic function. The coefficient assumes values between -1 (where $\frac{dy}{dx} < 0\ x \in \mathbb{R}$) and +1 (where $\frac{dy}{dx} > 0\ x \in \mathbb{R}$), the extremes reached when one of the variable is a perfect monotone of the other. A correlation coefficient of zero indicates there is no tendency for y to increase or decrease as x increases. So, if x and y are the variables to correlate, xi and yi are the ranked values, then the Spearman's correlation coefficient can be calculated from:

$$\rho = \frac{\sum_i (x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum_i (x_i - \bar{x})^2 \sum_i (y_i - \bar{y})^2}}$$

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