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Visitor Flows at a Large-Scale Cultural Event: GPS Tracking at Dutch Design Week

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Abstract: Large-scale cultural events bring many economic, social, and cultural benefits to the hosting cities. Although event producers aim to satisfy the visitors' needs, they do not usually receive feedback on visitors' experiences. Moreover, lack of spatial dispersal of visitors might result in less visibility for some activities and locations. An understanding of visitors' spatial and temporal behavior and the factors influencing visitors' intra-event destination choices is key to efficient and successful event management and future planning. In this article, we examine the relationship between visitors' spatial and temporal behavior, the spatial structure of the host city, and visitor characteristics. In order to do this, data are collected from 281 event visitors by means of GPS tracking and paper surveys at the Dutch Design Week (DDW) 2017 event in Eindhoven, the Netherlands. Data are used to understand the area of interest locations, visitor flows, visitor clusters and area of interest choices by applying data processing, network analysis, cluster analysis and bivariate analysis. The results show that one of the three dedicated event areas was considerably less popular by the DDW visitors. Moreover, the choice of intra-event destination locations and areas depended mainly on temporal constraints of the visitors. The findings of this study can inform future event planning and management policies in hosting cities.

Keywords: GPS tracking; event visitors; spatial analysis; visitor spatial behavior; cultural events; visitor flows; network analysis

1. Introduction

Large-scale cultural events and festivals in cities are recognized as significant tools for building the city image and attracting visitors [1]. Such events and festivals bring economic, social and cultural advantages to cities which then can be used to (re)generate places for better living, working and visiting conditions. Cities and event organizers have the responsibility to provide positive experiences for visitors in order to improve visitor satisfaction and stimulate repeated visits [2]. Large-scale events usually result in short-term fluctuations in the city's population because of the influx of visitors [3]. Fluctuations in the city's population might have an impact on the infrastructure and logistics, and cause negative experiences for visitors and residents (i.e., visitor congestion or overcrowding due to the promotion of already prominent public spaces and environmental deterioration due to litter and noise). Moreover, if visitors are not well navigated during an event, only the prominent locations of the city are frequented by the visitors and therefore not all exhibition locations may be visited. This might result in less economic, social and cultural advantages for these places.

During large-scale cultural events that are distributed to different areas in a city, it is difficult to obtain comprehensive feedback on visitors' flows. Having such feedback can help understanding visitors' spatial and temporal behavior, intra-event destinations and their relations and intra-event destination choices during the event. Consequently, diverse suggestions can be provided to visitors and event providers for better organized events and even distribution of visitors. Therefore, in order to evaluate the organization of the event and to develop sustainable policies for event tourism, it is vital to investigate visitors' flows during large-scale events [4].

In the last two decades, due to the increase in the availability of information and communications technology (ICT) tools (i.e., smartphone apps) and location positioning systems (i.e., global positioning system (GPS)), data-driven research on tourism and tourist flows has increased [5,6]. These technologies allow for capturing the mobility patterns of individuals, episodes and location of activities, the points of interests and the topology of activities in relation to the urban environment. According to Shoval and Ahas (2016) [6], the advantages of collecting data using GPS loggers and/or GPS-enabled smartphone apps are that they provide high-resolution data in time and space; they do not depend on respondents' memory, thus providing more accurate data; and they reduce the burden on participants as the data collection is less dependent on the respondents. However, such data lack respondents' background information such as socio-demographics, or sentiments about certain subjects. Therefore, GPS tracking is usually accompanied by online and/or paper surveys.

Current data-driven tourism studies focus on experiences and flows of tourists in a variety of settings such as touristic visitors in focal points within cities (i.e., ports, heritage districts, city centers) [7–11], visitors of recreational parks and zoos [12–14], and visitors of events [2,3,15–19]. By using the newly available datasets derived from ICT tools, these studies investigate visitors' perception of space and, also their behavioral patterns in time and space and the factors influencing these patterns such as socio-demographics characteristics of visitors (i.e., age, gender), spatial characteristics of visit location (i.e., origin of visit, location and centrality of attractions, accessibility of attractions) and time characteristics of the visit (i.e., starting time of visit, time at attractions). For instance, De Cantis et al. (2016) [9] state that visitors' age, gender, travel company and visitation frequency (being first- or second-time visitor) influence their visit patterns in port areas and therefore these characteristics can be used to segment visitors. A recent study from Gong et al. (2020) [19] focuses on the behavior of visitors of the Sail event and King's day in Amsterdam by using location-based social media data. This study shows that visitors differed in terms of their age and gender for their social media uploads per attraction. Moreover, Birenboim et al. (2013) [12] state that visitors' temporal patterns in theme parks are influenced by their time budget and also the park's controlled environment (i.e., opening hours and show schedules). Furthermore, Shoval et al. (2011) [7], Aranburu et al. (2016) [10], and Sugimoto et al. (2019) [11] show that due to distance decay, visitors' movements are largely limited by the starting location of their visit and the spatial configuration of attractions play a role in the choice of visits to intra-destinations.

These studies have implemented various techniques in order to detect and visualize movement patterns from location-based datasets such as grid-based aggregation [7–9], density-based clustering [19] and network analysis [3,10,11]. Grid-based aggregation and density estimation are usually used to identify the points of interest (POI)/area of interest (AOI) and network analysis are used to identify the relations between POIs/AOIs. The results of these studies contribute to policy formulations for destination planning and management, event impact management and transportation planning in touristic places.

Hitherto, most of the current studies on understanding large-scale events with newly available datasets [2,15–17] focus on subjective experiences of visitors and do not consider visitor flows during the event. Only few studies [3,18,19] highlight the visitor's spatial and temporal behavior in the large-scale cultural event setting by using Bluetooth, mobile network data and location-based social media data, respectively. This shows that there is a need for more studies on the large-scale cultural events in terms of understanding the visitors' flows (visitor's spatial and temporal behavior, intra-event destinations and their relations, and the factors influencing the intra-event destination choices) [18,20,21]. Moreover, the data collection of these studies [3,18,19] did not aim specifically at collecting data from event visitors, and therefore their data collection methods suggest more opportunistic approaches [22] such as scraping data from social media, rather than interacting with the visitors. This current study contributes to the existing studies on visitor's flows during large-scale events in terms of its GPS data collection methodology and analysis.

In this study, the aims are two-fold: (i) to understand the spatial and temporal behavior of visitors during the event, including the relations between intra-event destinations, and (ii) to understand the determinants of visitors' intra-event destination choices. For the first aim, we used the GPS data of 281 visitors in order to identify visitors' intra-event destinations, which refer to the areas of interest (AOIs). These AOI locations are determined based on places where visitors spend a certain amount of time (i.e., longer than 3 min) within a 100 m radius and how much the location is frequented by visitors. Then, we looked at the distribution of these AOIs in the city and how much time visitors have spent on average at these AOIs. Next, we applied network analysis in order to understand the relations between the visitations of each AOI. For the second aim, we combined the GPS data of visitors with their socio-demographics and applied bivariate analysis and cluster analysis.

This study is conducted within the framework of the European Union Horizon 2020 ROCK (regeneration and optimization of cultural heritage in creative and knowledge cities) project which aims to develop an innovative, collaborative and circular systemic approach for the regeneration and adaptive reuse of historic city centers. In this project, large-scale events are exploited as one of the enablers of sustainable urban transformation.

This paper is organized as follows: First, the case study area, data collection procedure and sample characteristics are explained. Then, the methodologies that are used to analyze the data are introduced. After that, the findings of the study are explicated. The paper concludes with the discussion of findings and the effectiveness of the methodologies for understanding visitor flows at large-scale cultural events, and with suggestions for event organizers and policy makers.

2. Materials and Methods

For this study, data collection was done in the course of a large-scale cultural event by means of GPS tracking and surveys. This section will firstly introduce the case study and its area. Then, it will describe the data collection procedure and the sample characteristics. Finally, the methods that were used for data processing and analysis will be explained.

2.1. Study Area

The case study of this research is the Dutch Design Week (DDW) event in 2017 in Eindhoven, the Netherlands. Eindhoven has a population of about 225,000 residents and is located in the south of the Netherlands. DDW is an annual event and it was conducted for the 17th time in 2017. It started on 21 October and lasted for 9 days with exhibitions, workshops, seminars and parties at approximately 80 different venues in the city. The event required the visitors to possess a ticket. The design works of 2500 designers were exhibited and approximately 300,000 people visited the exhibitions [23]. The venues were places both indoors (i.e., institutional buildings, private café and restaurants) and outdoors, and were distributed over three areas in the city, namely the Center area, Strijp-S area and East area. Figure 1 shows the exhibition locations within the three areas in Eindhoven. In terms of exhibition contents of areas, the Center area focuses on more traditional design products, Strijp-S is a more innovative and industrial design focused area and the East area is the new alternative design location of Eindhoven.

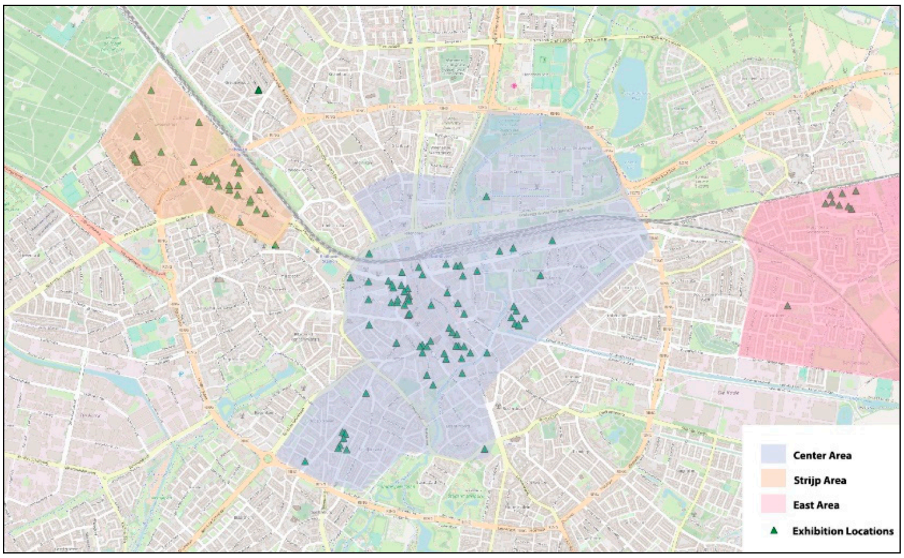

Figure 1. Location of exhibitions and areas [2].

DDW is organized in order to communicate the innovative outcomes of the city's significant companies (i.e., Philips, DAF, ASML) and institutes (i.e., Eindhoven University of Technology, Design Academy), as well as to increase collaboration between them. This event has an important role in Eindhoven's branding as the city's goal is to lead the digital industry and become the design capital.

2.2. Data Collection Procedure & Sample Description

The data were collected during four different days of the event in October 2017. Respondents were approached next to the ticket office, which was located near the central train station. This location was chosen since it was the main entrance point to the city and the event for many visitors. Respondents were recruited starting from 9:00 AM. In order to collect data on event visitors' characteristics and their spatial behavior, we applied a mixed approach of using GPS devices and questionnaires. Respondents were given a GPS logging device, which enabled recording visitors' routes every 3 s.

Before the experiment, the participants were first asked to fill in a questionnaire about their socio-demographic background, and their familiarity with the event and familiarity with the city. Then, they were asked to carry a GPS device and fill in a second questionnaire about their subjective experiences during their visits at the event. In this study, only the first survey on the visitor characteristics and the logs from GPS devices are used. In another article [2], we used the data related to subjective experiences of visitors.

A total of 317 respondents returned GPS devices but after cleaning the data, GPS logs of 281 respondents were found to be useful for this study. A total of 69 respondents were registeredon 21 October 2017, the first day of the event, 56 respondents on 24 October 2017, 68 respondents on 26 October 2017 and 88 respondents were registered on 28 October 2017.

Table 1 shows the sample characteristics of respondents. The majority of the sample was female and younger than 30 years old, had a travel company (i.e., partner, children, friends or colleagues), and was familiar with Eindhoven. In total, 53% of respondents indicated to combine their visit with other activities; 56% of the respondents have never visited DDW event before; 40% of the respondents intended to spend less than 5 h at DDW; 56% of the sample visited DDW during the weekend; finally, 41% of respondents arrived at the event before 11 o'clock, 32% arrived between 11 and 13 o'clock and 27% arrived after 13 o'clock.

Table 1. Sample characteristics (n = 281).

Variable	Levels	Frequency	Percentage
Gender	female	175	62
	male	106	38
Age	≤30 years old	201	72
	>30 years old	80	28
Combining other activities	yes	148	53
	no	133	47
Travel company	alone	119	42
	with other(s)	162	58
Familiarity with Eindhoven	not at all	101	36
	familiar	180	64
Familiarity with DDW	never visited	157	56
	one or more times visited	124	44
Intended duration of visit	≤5 h	112	40
	>5 h	169	60
Day of visit	weekday	124	44
	weekend	157	56
Arrival time	before 11:00	115	41
	11:00 to 13:00	91	32
	after 13:00	75	27

2.3. Data Processing and Analysis Methods

GPS data were processed by the Trace Annotator algorithm which was developed by the Urban Systems and Real Estate Unit of Eindhoven University of Technology [24–27]. Trace Annotator translates the GPS data of individuals into activity-travel diaries through machine learning algorithms. It mainly involves a segmentation module to split GPS traces into activities and trips, and recognition modules to classify transportation modes and activity types. A Bayesian belief network was used to differentiate transportation modes based on the extracted indicators related to speed, acceleration, measurement accuracy of GPS and the spatial contexts such as distance to road. A visit activity is identified according to the time interval of three minutes between consecutive GPS logs. The location of an activity is determined based on the end time and the frequency of GPS points that appear within a diameter of 100 m. Based on the coordinates of an activity location, the algorithm connects the GPS points sequentially and matches to land use, point of interest data and transportation network data derived from Open Street Map (OpenStreetMap data version 2017, OpenStreet Map Foundation, Cambridge, UK). For this, the algorithm first searches the possible road segments around a GPS point and then identifies the most probable one. After that, the algorithm determines the transportation modes, and matches the chosen route to the transportation networks.

The final product which is the activity-travel diary, provides information on a person's origin and destination, duration at visited AOIs, transportation modes between the AOIs. The algorithm has been used and tested in different projects and for different studies, such as [28]. An example of a GPS Track for one visitor and its annotation by TA can be found in Figure A1 in the Appendix A.

Based on the activity-travel diaries, firstly, day of the week for the visit, start time of the visit, the most frequented AOIs and AOI's locations, visitors' duration at AOIs, and visitors' time of arrival to each visited AOIs were extracted. In addition to the experiment data, weather data (KNMI, the Royal Netherlands Meteorological Institute, De Bilt, The Netherlands) from a secondary source were collected. Temperature and the occurrence of rain data, which are available at hourly ranges, were matched with the arrival time to each visited AOIs. Weather data were added to this study since they were found to be influential on visitors' location choice in urbanized areas [29,30]. Finally, these data were matched with the visitor characteristics.

2.3.1. Spatial and Temporal Behavior of Visitors

For understanding the spatial and temporal behavior of visitors, firstly the GPS logs were visualized in 100 m hexagons. This was done to understand where the GPS logs are clustered and whether these locations represent the output of Trace Annotator. In this study, based on the results of Trace Annotator outputs, 17 AOIs were considered since these were the most frequented ones (only the AOIs that were frequented by more than 25 visitors, were considered in this study in order to enable statistically significant results). Then, the average durations per AOI were calculated and represented on a map.

After that, in order to understand the relations between AOIs, a network analysis was performed on the origin-destination and intra-event destinations of each visitor. Network analysis, which is derived from graph theory, attempts to describe the relationships between given nodes. In the network analysis, a network is mainly composed of a set of nodes and links (formally called edges). It calculates the degree of centrality of individual nodes based upon their positioning within the network structure and measures their degree of connectedness depending on their links with each other, which contributes to the better understanding of the entire network [31]. In this study, nodes represent the origin of the trip, intra-event destinations (AOIs) and the final destination of the trip within the network and the edges represent the connections between the nodes. Thus, a network analysis can be used to examine the relationships between spatial entities.

In this study, from the outputs of Trace Annotator, an origin-destination matrix was produced and used for the network analysis. The nodes were defined as the visited AOIs of each DDW visitor, and the links represented the visitors' movements between the AOIs. In network analysis, it was considered that there is a relationship between two AOIs if a visitor went to both of them. In this study, the network of AOIs was applied as directed and weighted, and the results gave the measures for the centrality of AOIs.

One of the main applications of network analysis is the identification of central nodes in the network [32]. The most prominent nodes occupy central locations within the network. For network analysis, the most common four forms of centrality are identified [33,34] as degree, betweenness, closeness and eigenvector centrality. The measures of centrality quantify the importance of nodes. The identification of central nodes and the relation between them allow us to understand the importance of the nodes and the connectivity between different nodes.

Degree centrality measures the centrality of a node regarding the amount of direct connections to this node. The higher the degree, the higher the centrality of the node is. This usually reveals whether a node is a focal destination such as origin, core or terminating destination of a route [30]. Betweenness centrality measures the number of times a particular node lies on the shortest path between various other nodes in the set of nodes [35]. This indicator represents the ability of a given node to bridge interaction between pairs of other nodes in the network. For a large-scale event, high betweenness centrality of an AOI means that the AOI is a significant intermediary between pairs of other AOIs, because many visitors will stop at that AOI between visitations of other AOIs. Closeness centrality scores the closeness of a node to other nodes in the network, not only to the immediate neighbors [36], by including both direct and indirect links to the node. It calculates the shortest paths among all nodes and assigns each node a score depending upon its sum of shortest paths. The highest possible closeness centrality score is equal to 1, which indicates that a node is directly connected to every other node within the network [37]. For a large-scale event, high closeness centrality of an AOI means that AOI is reachable and close in distance amongst other AOIs. In addition to these, eigenvector centrality is calculated. Eigenvector centrality measures the importance of a node in a network by considering how well connected a node is and how many links their connections have. This calculation relies on the eigenvector centrality of the other nodes in the network that a node has receiving links with [38]. The eigenvector centrality measure has a range between 0 and 1, where 1 refers to a highly important node. For a large-scale event, high eigenvector centrality means that an AOI is important and well connected with other important AOIs (with high eigenvector values). However, it does not necessarily mean that this AOI is frequented many times. For this study, network analysis and visualization were carried out in Gephi software version 0.9.2.

2.3.2. Determinants of Intra-Event Destination Choices

Firstly, we looked into each AOI and investigated whether visitor characteristics, day of the week, start time of the visit, duration at AOIs, arrival time to AOIs, temperature and occurrence of rain at the time of visiting AOI influence visitors' choices of AOI. In order to do so, bivariate analysis was conducted, namely Pearson chi-square.

After that, K-means clustering analysis was performed in order to find out whether there were clusters among the visitors for their AOI choices. The K-means clustering method is an unsupervised machine learning algorithm that aggregates data points which have certain similarities and uses iterative refinement to produce a final result [39,40]. The algorithm inputs are the number of clusters K and the data set. The data set identifies for each visitor whether each AOI was visited. The algorithm starts with initial estimates for the K centroids. The algorithm then iterates between two steps. In the first step, each data point is assigned to its nearest centroid, based on the squared Euclidean distance. When all the data points are assigned to a cluster, the first step ends. In the second step, the centroids are recomputed. This is done by taking the mean of all data points assigned to that centroid's cluster. The algorithm iterates between steps one and two until the algorithm converges to a result. In this study, bivariate analysis was done between the found AOI clusters and visitor characteristics in order to investigate the differences between visitors that belong to different clusters. All analysis of this section was performed via SPSS Statistics 25 software package.

3. Results

This section will firstly introduce the results of spatial and temporal behavior of visitors, including the network analysis findings. Then, the results for the determinants of intra-event destination (AOI) choices will be given.

3.1. Results of Spatial and Temporal Behavior of Visitors

In order to visualize the distribution of GPS logs, the case area was divided into 100 m hexagons. Figure 2 shows the distribution of GPS logs in space. According to the outputs of the Trace Annotator algorithm, the most frequented areas of interest (AOIs) were calculated. Table 2 represents the most visited AOIs by the visitors of the sample of this study, indicating the percentage of visitors and the mean duration of visits at each AOI. Moreover, Figure 3 represents the same information spatially. All the AOIs correspond to one or a cluster of exhibition locations.

It is important to note that the participants were recruited at the Central Station (C1) and most of the participants also brought the GPS loggers back to this location. This explains the high number of visits and visitors for the "Central Station" AOI. Moreover, it is seen that all AOIs were located only in Central and Strijp-S areas, meaning that there was no AOI in the East area.

In Figure 3, it is seen that the most frequented AOIs were Central Station (C1) and Design Academy (C2), followed by Apparaten Fabriek (S1), Machinekamer (S2), Beukenlaan (S3) and Market Square (C3). Moreover, the average duration of the visit was the longest for the Design Academy (C2) and this is followed by Piet Hein Eik (S5), Beukenlaan (S3), Machinekamer (S2) and Temporary Art Center (C7), while 18 Septemberplein (C4), Central Station (C1) and Philips Museum (C11) were the least time spent locations. For the ease of reading, only the code of the AOI names will be mentioned from here on.

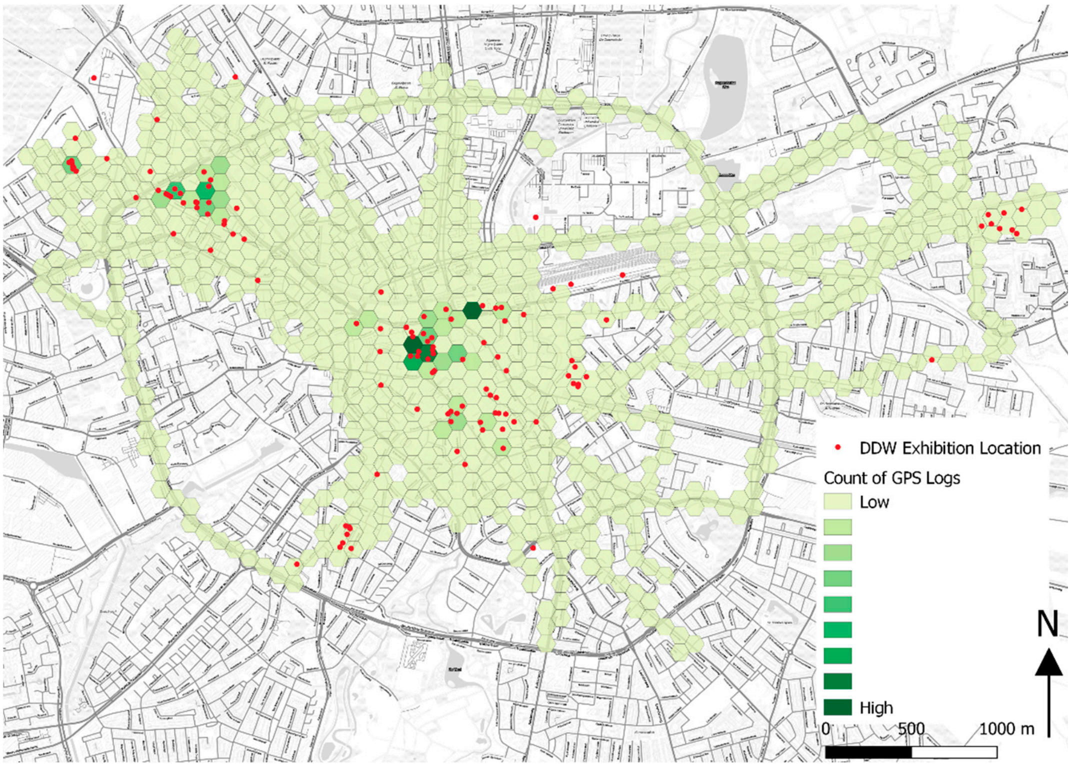

Figure 2. Distribution of GPS logs in 100 m hexagons and the location of DDW exhibitions.

Table 2. Visitation frequency and average time spent at areas of interest (AOIs).

AOI Name	Code	Area	% of Visits	Average Duration	Standard Deviation of Duration
Central Station	C1	Central	33%	20	55.17
Design Academy	C2	Central	14%	76	58.48
Market Square	C3	Central	6%	34	37.70
18 Septemberplein	C4	Central	5%	18	16.96
Rembrandt Bioscoop	C5	Central	4%	26	30.99
Café A	C6	Central	3%	29	51.59
Temporary Art Centre	C7	Central	2%	59	41.92
Het Klein Theater	C8	Central	2%	50	48.24
Van Abbe Museum	C9	Central	2%	51	30.51
Popocatepetl	C10	Central	2%	40	41.53
Philips Museum	C11	Central	2%	25	39.70
Stadhuisplein	C12	Central	2%	26	19.36
Apparaten Fabriek	S1	Strijp-S	7%	54	66.41
Machinekamer	S2	Strijp-S	6%	60	56.41
Beukenlaan	S3	Strijp-S	6%	66	51.09
Klokgebouw	S4	Strijp-S	3%	36	35.91
Piet Hein Eik	S5	Strijp-S	2%	71	48.64

Figure 3. Average duration of visitors in minutes at each AOI. Note: The size of AOIs is proportional to the number of visits (the larger an AOI is represented, the more frequented it was).

Network Analysis: Intra-Event Destinations and Their Relations

The centrality indicators resulting from the network analysis can be seen in Table 3. Regarding degree centrality, C1 has the highest degree, as expected. Since it was the origin of all visitors and final destination of the majority of visitors. This is followed by C2, C3, C5, S2 and S1. These AOIs can be considered as the high attraction points for the visitors. Looking at the betweenness centrality amongst all AOIs, again C1 has the highest value and this is followed by C3 and C2 with high scores (>8.8). This means these AOIs were significant intermediary locations between pairs of other AOIs, because many visitors might have stopped at C1, C2 and C3 between their visitations of other AOIs. Considering closeness centrality, all AOIs have a high closeness centrality value (>0.6). This means that the majority of AOIs were reachable and in close distance from other AOIs. C1, C2, C4, C5, C3 and S3 have the highest scores, respectively, which signify that they have the shortest distances to all other nodes. The closeness indices above 0.6 might also indicate that the connections between AOIs in terms of mobility options provided were convenient. Finally, looking at the eigenvector centrality, again all AOIs perform above 0.5. The high scores for AOIs C1, C3, C2, S1, S2, C5 and S4 indicate that they were significant AOIs and also were well connected with other significant AOIs. An interesting finding is that, although S4 has relatively low scores for degree, betweenness and closeness centrality measures compared to the majority of other nodes in the network, its eigenvector centrality score is high. This might mean that S4 was not an interesting location for visitors but it received direct links (visitors) from important AOIs such as C1, C2 and S1. An explanation for this could be the nearby train station of Strijp-S and the DDW bus stop.

Table 3. Results of centrality indicators of network analysis.

AOI Code	Degree	Betweenness	Closeness	Eigenvector
C1	34	10.908	1.000	1.000
C2	33	8.865	1.000	0.935
C3	31	9.331	0.842	1.000
C4	26	4.904	0.889	0.738
C5	29	5.753	0.889	0.838
C6	19	1.323	0.727	0.553
C7	19	1.228	0.727	0.579
C8	21	2.421	0.727	0.683
C9	22	3.124	0.842	0.559
C10	23	2.382	0.762	0.653
C11	20	2.678	0.800	0.535
C12	19	1.914	0.727	0.550
S1	27	3.690	0.762	0.902
S2	28	5.236	0.800	0.882
S3	26	5.321	0.842	0.728
S4	22	1.547	0.640	0.815
S5	19	1.376	0.667	0.672

A directed network of visitor flows (in-strength), constructed based on the origin-destination matrix, is illustrated in Figure 4. The size of the AOIs is proportional to the degree of centrality measurement. The color of AOIs represents the betweenness centrality value (the darker the color, the higher betweenness centrality) and the color of the links represents the weight of the link (the darker the color, the higher the weight of a link). The directed network shows that, in the central area, C1, C2 and C3 were well connected AOIs. After being at C1, the majority of visitors went to C2, and the rest visited mainly either C3, C4 or other AOIs in the city center. Moreover, the majority of visitors entered the Strijp-S area at S1, coming mainly directly from C1 and then visited the other AOIs in the Strijp-S area. After their visits to AOIs in the Strijp-S area, most of the visitors returned back to C1.

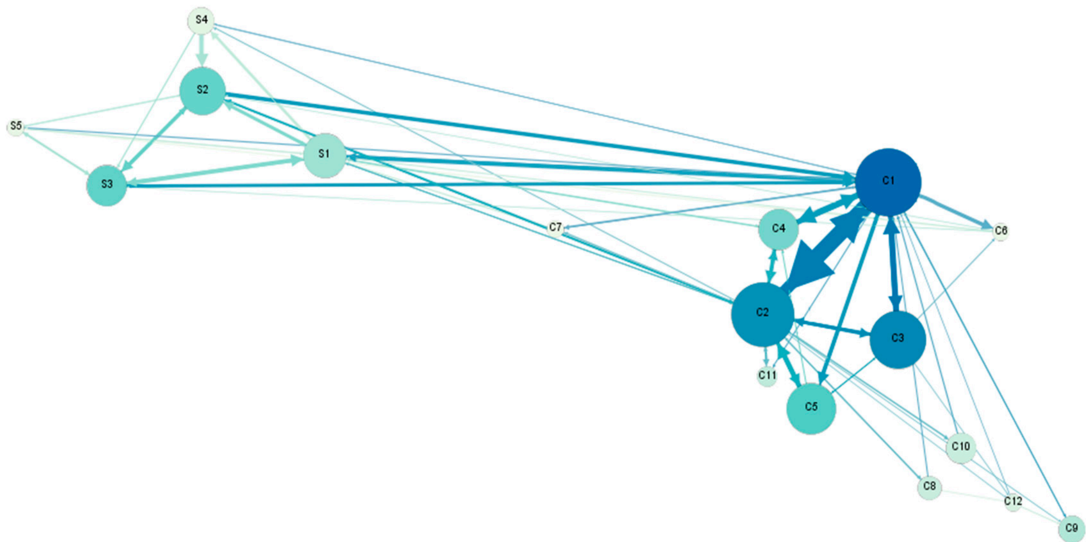

Figure 4. Directed network of visitor flows.

According to the results of this section, during DDW, C1 was an important node as expected since it was the starting point (origin) for the visitors in our sample. Moreover, it is seen that C2 was an important AOI due to its high centrality indicators. Moreover, the high average duration spent at this node indicates that C2 was the most attractive event location for the visitors. In addition to this, looking at the centrality indicators and average duration spent at the AOIs, C3 was also an important and attractive event location. Moreover, C5 has high centrality indicators; however, the average duration for that AOI was not as high as C2 and C3.

Since all these AOIs are located in the central area, it is also useful to look into the AOIs in the Strijp-S area separately. Amongst the AOIs within the Strijp-S area, S1, S2 and S3 have the highest centrality indicators, suggesting that these AOIs were significant and connected ones within the area. In addition, the average time spent at these AOIs was similar, suggesting that these AOIs were the most attractive ones within the Strijp-S area during the DDW. Finally, it can be said that although S4 was not an attractive AOI, it received direct visits from important and interesting nodes (high eigenvector centrality); therefore, it can be considered as an important AOI in the Strijp-S area.

3.2. Results for the Determinants of Intra-Event Destination (AOI) Choices

After determining the AOIs, the influence of visitors' characteristics and the AOI-specific characteristics on the visitors' choice of AOIs was investigated. C1 (central station) was removed from the analysis since it was the origin of the trip and not an intra-event destination. The data and results can be seen in Table A1 in Appendix A.

According to the results, age of visitors shows a significant result at the 10% significance level (X^2 (NDF = 15, n = 1120) = chi-square 23.350, p = 0.077), meaning that there were significant differences between the choice of AOIs for different age groups. The results show that C7, C9 and S4 were preferred more by visitors below 30 years old, while S5 was preferred by visitors older than 30 years old. This might be related to the content of exhibition within this AOI and also the atmosphere of the area related to the services around. Moreover, there is a significant association between the intended duration of the event visit and the choice of AOI, at 10% level (X^2 (NDF = 15, n = 1120) = chi-square 22.606, p = 0.093). People who intended to visit the event more than 5 h preferred to include mostly C7 and C9 to their visits. In terms of distance, AOIs C7 and C9 are relatively further from the city center and the origin of the visit (C1). Thus, it can be said that visitors who had more time for DDW visitation preferred to include further locations to their itinerary.

In terms of AOI-specific characteristics, arrival time to each AOI shows significant association with the choice of AOI (X^2 (NDF = 15, n = 1120) = chi-square 39.178, p = 0.001). The results indicate that most of the visitors preferred to visit the AOIs in the central area before 13:00. Moreover, the duration at AOI has a significant relationship with the choice of AOI (X^2 (NDF = 15, n = 1120) = chi-square 184.092, $p < 0.001$). Especially at C2, C7, S3 and S5, most of the visitors tended to spend more than 45 min. These AOIs included several exhibitions which were represented in large spaces. This might have caused the longer time spent at these AOIs. Finally, it is found that occurrence of rain at arrival time to AOI shows a significant relationship with the choice of AOI, at 10% level (X^2 (NDF = 15, n = 1120) = chi-square 22.604, p = 0.093). When there was rain, C2, S2, S3 and S4 were the most preferred AOIs. This might be because C2 included several exhibitions in a large and closed space. S2, S3 and S4 were similar in that sense and, in addition, these AOIs contain several eating and drinking services such as cafes and restaurants.

These results denote that intra-event destination (AOI) choices of DDW visitors depended on the visitors' age, their intended duration for their visit and AOI-specific characteristics, namely, arrival time to AOI, duration at AOI and the occurrence of rain at the arrival time to AOI. It is found that the association was highly significant between AOI choice and AOI-specific characteristics, especially for temporal aspects. The reasoning behind these choices might be explained with the characteristics of the exhibitions in these AOIs, and also the spatial characteristics of these AOIs in terms of the services provided and the type and size of exhibition buildings.

Clustering of Intra-Event Destination (AOI) Choices

In order to understand whether there were clusters amongst DDW visitors based on their AOI choices, K-means cluster analysis was performed. The number of clusters was decided to be two after several trials. For two clusters, convergence was achieved at the 8th iteration. The two clusters of AOIs can be seen in Figure 5 and their spatial distribution can be seen in Figure 6a,b. Cluster 1 contains 115 visitors, Cluster 2 contains 166 visitors. An analysis of variance (ANOVA) test was conducted in order to check the differences between the clusters (See Appendix A, Table A2). According to this test, visitors' choices on visiting C4, C7, C8, C9, C11, C12 did not differ significantly between the clusters (at 10% significance level). As can be seen in Figure 5, Cluster 1 contains visitors that visited mainly the AOIs in the Strijp-S area who also visited some of the AOIs in the Central area, largely C2. Cluster 2 consists of visitors that visited the AOIs mainly within the Central area and rarely combined their visit with the Strijp-s area.

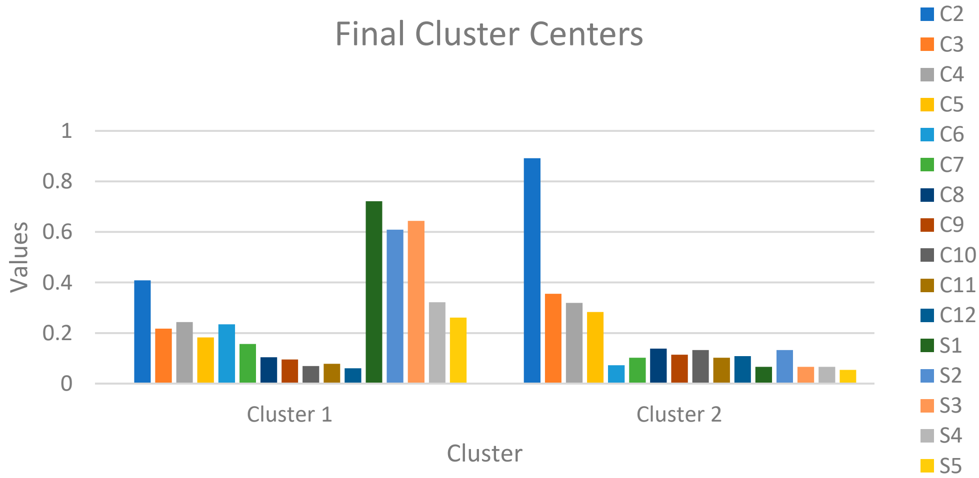

Figure 5. Distribution of AOI visits per clusters.

(**a**) (**b**)

Figure 6. Spatial distribution of AOI visits per clusters: (**a**) Cluster 1, (**b**) Cluster 2.

Table 4 shows the results of chi-square analysis between the determined clusters and the visitor characteristics. According to the Pearson chi-square test, there is a significant difference between the clusters in terms of visitors' arrival time to DDW event. The results show that the majority of the visitors who are in Cluster 1 preferred starting the event activity early (before 11:00 am). It is possible that visitors considered time restrictions for their visit before the event started so that their visit could cover both areas. It is also possible that visitors who arrived early decided to visit both locations considering the spatial organization of the event. Visitors who are in cluster 2 (tended to mainly visit the Central area) did not show a strong preference for the arrival time to DDW.

Table 4. Results of the chi-square test between clusters and visitor characteristics (within cluster percentages of the number of visitors are in brackets).

Variables	Levels	Cluster 1	Cluster 2	Pearson Chi-Square		
				Value	df	Asymptotic Significance (2-sided)
Gender	Female Male	69 (60.0%) 46 (40.0%)	106 (63.9%) 60 (36.1%)	0.430	1	0.512
Age	≤30 years old >30 years old	79 (68.7%) 36 (31.3%)	122 (73.5%) 44 (26.5%)	0.768	1	0.381
Combining Other Activities	Yes No	58 (50.4%) 57 (42.9%)	90 (54.2%) 76 (45.8%)	0.390	1	0.532
Travel Company	Alone With other(s)	46 (40.0%) 69 (60.0%)	73(44.0%) 93 (56.0%)	0.440	1	0.507
Familiarity with Eindhoven	Not at all Familiar	41 (35.7%) 74 (64.3%)	60 (36.1%) 106 (63.9%)	0.007	1	0.933
Familiarity with DDW	Never visited One or more times visited	63 (54.8%) 52 (45.2%)	94 (56.6%) 72 (43.4%)	0.094	1	0.760
Intended Duration of Visit	≤5 h >5 h	45 (38.6%) 70 (61.4%)	67 (40.4%) 99 (59.6%)	0.088	1	0.767
Day of Visit	Weekday Weekend	48 (41.7%) 67 (42.7%)	76 (45.8%) 90 (54.2%)	0.451	1	0.502
Arrival Time	Before 11:00 11:00 to 13:00 After 13:00	61 (53.0%) 32 (27.8%) 22 (19.1%)	54 (32.5%) 59 (35.5%) 53 (31.9%)	12.403	1	0.002

4. Discussions and Conclusions

Research on visitors' flow during large-scale events is still limited but highly important for event planning and management, transportation development and impact management. This study contributes to the few existing studies on large-scale events in terms of its data collection with GPS loggers and a survey, and the analysis of the data for understanding the visitor flows and visitors' intra-event destination choices.

Although the city dedicated three areas for the DDW, only two of them (Central and Strijp-S) were visited enough to be considered to have AOIs. The results indicate that visitors of DDW preferred AOIs in the Central area and Strijp-S (West) area, rather than in the East area of the city. The East area is a new 'alternative design' district of the city. Since this area's concept for design is new, it was less known to DDW visitors compared to the Center and Strijp-S areas. Moreover, the most attractive AOIs, which are C2 and C3, are in the highly central and busy district of the city, close to each other, to the central train station and to other activities and services such as shops, cafes and bars. The same applies to the most attractive AOIs of Strijp-S area which are S1, S2 and S3. Moreover, it is found that the Central area and Strijp-S area are connected to each other, especially by the flow of visitors between C1 to S1. These results show that the high attraction points of the city were again the most significant ones during the DDW event. Moreover, the distance decay factor might have influenced the flows to far locations within the areas. This might also be a reason for the limited attractiveness of the East area. In order to distribute the flows to other less represented locations, exhibition contents and their locations should be reconsidered in the future events. Additionally, the distance decay factor can be eliminated by strengthening the provision of a variety of mobility options (i.e., busses and bikes associated with the event) in many of the AOIs. The lack of spatial dispersal of visitors might also be due to the need for a clearer wayfinding system in terms of maps, roads and transport signs. Improvements in these aspects can support the visitors to find their way and explore different locations of the city during the DDW event. For that purpose, city managers should make an on-site assessment of the current navigation services.

The intra-event destination (AOI) choices were mainly influenced by visitors' age, visitors' intended DDW visit duration, arrival time to AOI, duration at AOI and rain occurrence at the arrival time to AOI. Visitors' age might have created a taste variance based on the content of exhibition at AOIs and the location and atmosphere of AOIs. Additionally, AOI choices of visitors were associated with time constraints. Time-related restrictions (such as starting time of the event) were influential also on the choice of exhibition areas. In order to maximize the time span of visitors and navigate the visitors through different areas based on visitors' tastes, themed trips of certain durations can be organized. These themed trips can include suggested itineraries for different themes and can be provided as maps and/or brochures at the ticket offices or as a smartphone app service.

This study proves that GPS data together with a survey is a valid approach for future studies on visitor flows at large-scale events. However, the data collection process is a limitation for recruiting larger numbers of respondents since people need to stop at the ticket office to answer the survey questions and be instructed regarding the GPS loggers. In addition, the distribution and collection of GPS loggers at a specific location is another limitation of this study since visitors who start the event visiting from another location might visit different AOIs. Therefore, this approach can be further advanced in future studies by developing a dedicated user-friendly smartphone application. This app can also accommodate questions regarding visitors' choices for AOIs. Another limitation of the study was that we considered a place an AOI if it was frequented by more than 25 visitors. The reason for that was to conduct bivariate analysis with enough samples of visitors. However, this might have caused bias for the network representation because there might have been other places visited and included in the origin destination matrix. It was also surprising that visitor characteristics (except age and intended duration of visit) were not found to be significant. This might be because the surveyed characteristics were not differentiating or because our sample was homogenous. This should be further examined in a future study.

Overall, this study provided useful insights for event managers and city planners for better organized events. It shows that understanding visitors' flows at large-scale events can reveal how much of the space is consumed by different visitor profiles, and therefore the level of attraction of different locations in the city. With the suggestions provided in this study, large-scale events such as DDW can increase the potential of exhibitions for more and repeating visitors. It will also contribute to further event planning for different target groups. In the future, this approach can be further extended for modeling scenarios to predict the results of different event interventions for better organized and sustainable events.

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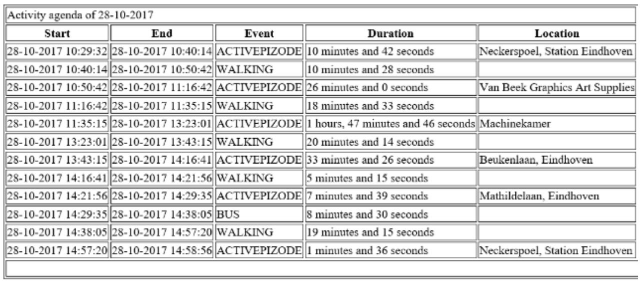
Conflicts of Interest: The authors declare no conflict of interest.

Ethical Approval: All subjects gave their informed consent for inclusion before they participated in the study.

Appendix A

Table A1. Results of the chi-square test between AOIs and visitor-specific and AOI-specific variables.

Variable		Levels	C2	C3	C4	C5	C6	C7	C8	C9	C10	C11	C12	S1	S2	S3	S4	S5	Pearson Chi-Square		
																			Value	Df	Asymptotic Significance (2-Sided)
Visitor-specific variables	Gender	Female	151	59	61	51	27	24	22	20	25	13	13	68	65	52	30	21	17.009	15	0.318
		Male	80	36	27	23	15	12	14	10	7	15	13	45	40	44	19	18			
	Age	≤30 years old	168	69	65	52	28	29	22	25	19	18	17	81	73	59	38	19	23.350	15	0.077
		>30 years old	63	26	23	22	14	7	14	5	13	10	9	32	32	37	11	20			
	Combining Other Activities	Yes	111	51	38	32	19	21	18	14	21	13	11	60	46	38	26	16	14.699	15	0.473
		No	120	44	50	42	23	15	18	16	11	15	15	53	59	58	23	23			
	Travel Company	Alone	104	42	33	34	17	15	17	12	11	11	9	44	32	48	13	16	17.266	15	0.303
		With other(s)	127	53	55	40	25	21	19	18	21	17	17	69	73	48	36	23			
	Familiarity with Eindhoven	Not at all	88	40	32	36	20	12	13	9	12	13	12	41	38	35	20	13	9.348	15	0.859
		Familiar	143	55	56	38	22	24	23	21	20	15	14	72	67	61	29	26			
	Familiarity with DDW	Never visited	133	67	49	47	29	16	19	12	19	15	17	66	60	53	31	23	18.139	15	0.255
		One or more times visited	98	28	39	27	13	20	17	18	13	13	9	47	45	43	18	16			
	Intended Duration of Visit	≤5 h	85	29	42	27	21	6	11	8	13	13	6	43	43	36	15	15	22.606	15	0.093
		>5 h	146	66	46	47	21	30	25	22	19	15	20	70	62	60	34	24			
	Day of Visit	Weekday	96	36	43	33	27	13	13	14	9	13	9	40	41	42	25	17	19.962	15	0.173
		Weekend	135	59	45	41	15	23	23	16	23	15	17	73	64	54	24	22			
	Arrival Time to the Event	Before 11:00	101	51	33	36	15	19	19	15	19	11	14	60	64	57	31	23	35.372	30	0.229
		11:00 to 13:00	76	27	36	23	17	13	11	11	6	11	6	31	25	25	12	11			
		After 13:00	54	17	19	15	10	4	6	4	7	6	6	22	16	14	6	5			
AOI-specific variables	Arrival Time to the AOI	Before 13:00	147	45	47	45	26	16	21	15	14	16	9	51	39	45	19	18	39.178	15	0.001
		After 13:00	84	50	41	29	16	20	15	15	18	12	17	62	66	51	30	21			
	Duration at AOI	≤45 min	84	71	81	62	36	15	25	16	21	25	22	73	54	45	38	12	184.092	15	0.000
		>45 min	147	24	7	12	6	21	11	14	11	3	4	40	51	51	11	26			
	Occurrence of Rain	No	153	61	45	49	27	23	24	19	27	17	14	77	57	52	28	23	22.604	15	0.093
		Yes	78	34	43	25	15	13	12	11	5	11	12	36	48	44	21	16			
	Temperature	≤13.0 C	81	36	31	21	13	10	10	9	12	7	9	37	38	28	17	7	21.750	30	0.863
		13.1 to 16.0 C	91	34	40	26	21	15	14	13	9	13	9	39	38	37	19	19			
		>16.0 C	59	25	17	27	8	11	12	8	11	8	8	37	29	31	13	13			



Activity agenda of 28-10-2017				
Start	**End**	**Event**	**Duration**	**Location**
28-10-2017 10:29:32	28-10-2017 10:40:14	ACTIVEPIZODE	10 minutes and 42 seconds	Neckerspoel, Station Eindhoven
28-10-2017 10:40:14	28-10-2017 10:50:42	WALKING	10 minutes and 28 seconds	
28-10-2017 10:50:42	28-10-2017 11:16:42	ACTIVEPIZODE	26 minutes and 0 seconds	Van Beek Graphics Art Supplies
28-10-2017 11:16:42	28-10-2017 11:35:15	WALKING	18 minutes and 33 seconds	
28-10-2017 11:35:15	28-10-2017 13:23:01	ACTIVEPIZODE	1 hours, 47 minutes and 46 seconds	Machinekamer
28-10-2017 13:23:01	28-10-2017 13:43:15	WALKING	20 minutes and 14 seconds	
28-10-2017 13:43:15	28-10-2017 14:16:41	ACTIVEPIZODE	33 minutes and 26 seconds	Beukenlaan, Eindhoven
28-10-2017 14:16:41	28-10-2017 14:21:56	WALKING	5 minutes and 15 seconds	
28-10-2017 14:21:56	28-10-2017 14:29:35	ACTIVEPIZODE	7 minutes and 39 seconds	Mathildelaan, Eindhoven
28-10-2017 14:29:35	28-10-2017 14:38:05	BUS	8 minutes and 30 seconds	
28-10-2017 14:38:05	28-10-2017 14:57:20	WALKING	19 minutes and 15 seconds	
28-10-2017 14:57:20	28-10-2017 14:58:56	ACTIVEPIZODE	1 minutes and 36 seconds	Neckerspoel, Station Eindhoven

(**a**) (**b**)

Figure A1. (**a**) GPS track of one visitor; (**b**) Trace Annotator output of the GPS track of one visitor

Table A2. ANOVA analysis of final cluster centers.

AOI	Cluster		F	Significance
	Mean Square	**df**		
C2	15.840	1	100.809	0.000
C3	1.294	1	6.270	0.013
C4	0.390	1	1.902	0.169
C5	0.686	1	3.766	0.053
C6	1.794	1	15.741	0.000
C7	0.199	1	1.823	0.178
C8	0.079	1	0.726	0.395
C9	0.024	1	0.250	0.617
C10	0.269	1	2.833	0.093
C11	0.040	1	0.469	0.494
C12	0.154	1	1.896	0.170
S1	29.188	1	244.063	0.000
S2	15.403	1	92.469	0.000
S3	22.635	1	172.289	0.000
S4	4.434	1	34.979	0.000
S5	2.901	1	26.378	0.000

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