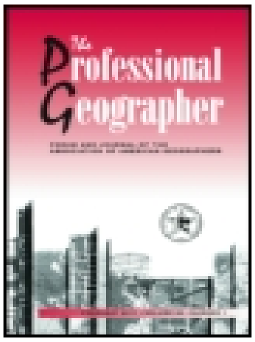

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Weighting the Effects of Spatial Cognition and Activity Anchors on Time–Space Activity

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Many elements are known to affect the decision-making procedures that underlie time–space activity patterns. Yet, knowledge regarding the relations between these elements is lacking. In this article, a hierarchical structure of external and cognitive time–space behavioral influences is proposed based on the results of a field experiment. The experiment relied on an in situ sampling of stated and overt behaviors of visitors to a touristic site in northern Israel, using questionnaires and Global Positioning System loggers. Two experimental treatments were simultaneously applied during sampling, dividing the sample into four groups: Each participant received on entry one of two maps, designed according to different cartographical–cognitive approaches; new activity stations were placed during half of the sampling days, meaning that each participant was exposed to one of two possible spatial layouts. The behavioral patterns recorded expose each treatment's distinct behavioral effect along with its relative weight within the decision-making process, thus pointing toward a hierarchical structure. **Key Words: activity anchors, Global Positioning System, spatial cognition, time–space behavior, tourist behavior.**

诸多因素被认识为影响支撑时空活动模式的决策过程, 但却缺乏有关这些元素间的关系之知识。本文根据田野实验的结果, 提出外在且认知的时空行为影响之阶层结构。该实验依赖以色列北方一处观光景点中宣称且明显的访客行为之原位抽样, 并运用问卷和全球定位系统记录器。抽样时同时运用两大实验方法, 并将样本分为四大群体: 各参与者在进入时获得根据不同製图认知方法设计的两张地图中的一张; 在抽样日期过半时置入新的活动站, 意味着各参与者暴露于两种可能空间安排的其中一种。本研究纪录的行为模式, 暴露出决策过程中, 各种方法随着其相对权重的特殊行为影响, 因此指向阶层化的结构。 **关键词: 活动定锚, 全球定位系统, 空间认知, 时空行为, 观光客行为**。

Muchos son los elementos que se sabe afectan los procedimientos de toma de decisiones que subrayan los patrones de actividad tiempo–espacio. No obstante, el conocimiento sobre las relaciones entre estos elementos es insuficiente. En este artículo se propone una estructura jerárquica de las influencias conductuales externas y cognitivas del tiempo–espacio, con base en los resultados de un experimento de campo. El experimento dependió de un muestreo *in situ* de conductas declaradas y públicas de visitantes de un sitio turístico en el norte de Israel, usando cuestionarios y registros del Sistema de Posicionamiento Global. Durante el muestreo, se aplicaron simultáneamente dos tratamientos experimentales, dividiendo la muestra en cuatro grupos: Cada participante recibió de entrada uno de dos mapas, designado de acuerdo con diferentes enfoques cartográfico–cognitivos; se colocaron nuevas estaciones de actividad durante la mitad de los días de encuesta, lo cual significa que cada participante estuvo expuesto a uno de dos posibles planos espaciales. Los patrones de conducta registrados exponen cada efecto conductual distinto del tratamiento junto con su peso relativo dentro del proceso de toma de decisiones, apuntando así hacia una estructura jerárquica. **Palabras clave: anclas de actividad, cognición espacial, conducta del tiempo–espacio, conducta del turista, Sistema de Posicionamiento Global.**

The study of spatial decisions carried out by various actors makes an important area of inquiry in many research fields (Golledge and Stimson 1997; McCormack and Schwanen 2011). Such choices are understood to be the outcome of an interplay between the characteristics of the decision maker, the external environment, decision-making procedures, and the inputs on which these procedures rely (Golledge and Stimson 1997; Chen et al. 2016). In accordance, any study of spatial behaviors demands some consideration of decision-making processes along with their relation to spatial realities.

A widely used model that describes these processes is that of the rational decision maker (Strauss 2008; Chen et al. 2016). Yet evidence collected since the 1950s suggests that this model is invalid in many cases (the most famous examples being Simon 1952, 1972; Kahneman and Tversky 1979). Starting from initial applications of nonrational models to spatial problems (e.g., Isard and Dacey 1962; P. R. Gould 1963; Wolpert 1964), a research branch studying spatial behavior using disaggregate data had developed (behavioral geography; Golledge 2008). As research continued, a need for a more systematic inspection of choice processes' knowledge base rose (J. R. Gould and Goodey 1983), propelling a cognitively based research of spatial behavior.

By now it is well established that a cognitive representation of the external world exists within the mind (Tolman 1948; Kirk [1952] 1989; Downs and Stea 1973; O'Keefe and Nadel 1978; Hafting et al. 2005). This representation (i.e., the cognitive map) is known to be multilayered in nature, where spatial information is overlaid with nonspatial knowledge (Lynch 1960; Kitchin 1994). Evidence shows that many systematic distortions exist within such representations, arising from limited

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perception and attention capabilities. For example, biases in distance and travel time estimations are attributed to the number of features en route, to the segmentation of paths, and to nonlinear perceptions of space (Sadalla, Staplin, and Burroughs 1979; Allen and Kirasic 1985; Montello 1997; Sargent et al. 2013; Brunyé, Mahoney, and Taylor 2015), and inaccurate judgments of relative location are related to the hierarchical organization of knowledge, abstract and real axial elements, or orientation (Stevens and Coupe 1978; Tversky 1981; Portugali and Omer 2003; Phillips and Montello 2015). Furthermore, as cognitive maps develop around central activity points (i.e., cognitive anchors; Golledge 1978), errors in the perception of these could be translated into large-scale cognitive biases (Couclelis et al. 1987; Manley, Addison, and Cheng 2015; Manley, Orr, and Cheng 2015). Such distortions are suggested to affect overt time–space behavior over several dimensions: perception of activity spaces' boundaries (Kwan and Hong 1998; Casceta, Carteni, and Montanino 2016), destination choices (Cadwallader 1975; Hannes, Janssens, and Wets 2008), transport mode choices (Hannes, Janssens, and Wets 2009), and wayfinding behaviors (Gärling 1989; Penn 2003; Guo 2011). Because these choices are related to each other, multilevel effects of cognition on time–space behavior exist (Gärling and Golledge 2000; Hannes, Janssens, and Wets 2008).

Yet, and despite these findings, a reoccurring critique of behavioral geography addresses its assumption that time–space behavior is preceded by conscious and deliberate decision-making procedures (i.e., behavior is volitional). This leads, according to this critique, to an insufficient consideration of precognitive components (Anderson and Smith 2001; Pile 2010) and of the extent to which social, cultural, institutional, and physical activity contexts dictate behavior (Desbarats 1983; Lundberg 1991; McCormack and Schwanen 2011; Pykett 2013). This latter issue is addressed within the framework of time geography (Hägerstrand 1970). By conceptualizing the body as an indivisible unit, this framework identifies time and space as limited and substitute resources at the disposal of individuals during their daily activities: Individuals are forced to constantly choose between carrying stationary activities (i.e., consuming time) and enlarging their opportunity set via movement (i.e., consuming space; Neutens, Schwanen, and Witlox 2011; Grinberger, Shoval, and McKercher 2014). Time geography stresses the constrained nature of time–space behavior, relating to time–space resource allocation choices as being carried within the limits of a time budget, which itself is defined based on external constraints and personal goals (Hägerstrand 1970; Long and Nelson 2013). From this it follows that individuals' activity spaces (represented by geometrical entities such as the time–space prism) are highly contingent on spatial layouts, their shape and size being sensitive to environmental changes such as the addition of activity anchors (Lenntorp 1976). A direct link thus exists between spatiotemporal layouts and actual behaviors.

Indeed, many environmental effects on time–space behavior have been identified so far, including those of origin location, nature of environment, number and location of activity points, and street shapes (Horton and Reynolds 1971; Buliung and Kanaroglou 2006; Fan and Khattak 2008; Shoval et al. 2011; Wang, Grengs, and Kostyniuk 2013; Parthasarthi, Hocmair, and Levinson 2015; Xu et al. 2016). Time geography was also used to study issues beyond the physical and the representational, such as cognitive, precognitive, and cultural effects (Kwan and Hong 1998; Kwan 2002, 2008; Latham 2003; Schwanen 2006; McQuoid and Dijst 2012; Grinberger, Shoval, and McKercher 2014), yet its constraints-based view leads many to treat individuals as nothing more than their trajectories, neglecting mobility's subjective element (Kwan and Schwanen 2016; Schwanen 2016). This conceptual difference between behavioral geography and time geography has prevented their full integration (Couclelis 2009; Neutens, Schwanen, and Witlox 2011), despite these theoretical stances potentially complementing each other, as evident, for example, in activity anchors' important role in shaping both activity spaces and their cognitive representation. Studying the relationships between the internal and the external is a challenging task, because it requires mapping behavior throughout the decision-making process and not just specific instances of it (McCormack and Schwanen 2011).

In this context, the development of advanced tracking techniques since the early 2000s (Shoval and Isaacson 2007; D. B. Richardson et al. 2013) offers some potential. By allowing sampling of time–space behavior in situ with great accuracy, studies using tracking techniques such as the Global Positioning System (GPS) have been able to assess the behavioral influence of elements like environmental settings (Guo and Loo 2013), "home" location (Shoval et al. 2011), previous experiences (McKercher et al. 2012), or planned route choices (Papinski, Scott, and Doherty 2009). Recently, several studies have shown how internal elements such as emotions, cognitive maps, and choice strategies could be reconstructed and studied using such data (Greenberg Raanan and Shoval 2014; Grinberger, Shoval, and McKercher 2014: Shoval, Schvimer, and Tamir 2018). Hence, using the right research design, such data collection methods could be used to simultaneously study environmental and internal effects over time–space activity.

This work aims to contribute to the bridging of the gap discussed earlier by studying how external conditions and their cognitive representations affect conscious decisions and specifically the weights these elements hold in the formation of behavior patterns. By doing so, the extent to which time–space behavior is indeed volitional is assessed. For this, this work employs GPS logger–based sampling of time–space behaviors within a controlled and regulated real-life environment, as part of a quasi-experimental research design. This field experiment included two interventions (treatments)—one affecting cognitive representations and the other altering the spatial layout—that were applied separately and simultaneously. This experimental approach promotes the identification of the distinct and combined effects of internal and external time–space behavioral dimensions and thus generates more accurate and detailed answers to important questions within the study of time–space behavior. The rest of the article is organized as follows: First, method and data are discussed; second, the results of the experiment are detailed; and, finally, a discussion of the theoretical implications of the results is presented and directions for future research are suggested.

The Experimental Design: Method and Data

Studying the role of specific variables within complex decision-making processes requires controlling for other variables' effects. In this context, experimental designs carried out within lab environments offer much utility. Yet such designs limit the transferability of results to real-life environments, because they study behavior removed from context. Sampling of behavior in situ, on the other hand, introduces much uncertainty into the data and limits the ability to control some variables. The quasi-experimental design employed here exploits the advantages of both approaches, by coupling an experimental design with the sampling of behavioral patterns within a controlled, yet real-world environment.

Study Area

The site selected for this research was the Memorial Gardens in Ramat Hanadiv, Israel, a garden complex built around the crypt of the Baron Edmund de-Rothschild[1] and his wife (Figure 1), which functions as a tourist attraction. This site offers several advantages in the context of this study. First, its size (17.30 acres) and design greatly reduce the influence of age, physical status, and time budget considerations on the formation of time–space activity patterns. Second, the site is large enough and the trails network is complex enough to make it impossible for the visitor to fully perceive the gardens' structure right on entry. In addition, except for a small number of signs posted near the entrance, the site offers no navigational aids to visitors. This is complemented by the fact that many visitors are not familiar with the gardens, meaning that they hold no clear cognitive representation of their structure. Consequently, many of the visitors must rely on intuition or navigational aids during their visit to the gardens. Finally, the environment within the gardens is highly controlled and regulated, meaning that activity is confined to a small number of trails and that unexpected events are highly improbable. These characteristics make the gardens a lab-like environment in which external conditions are controlled and behavioral patterns are highly contingent on the spatial layout and knowledge about it, making the site an optimal location for conducting investigations such as the one carried out here.

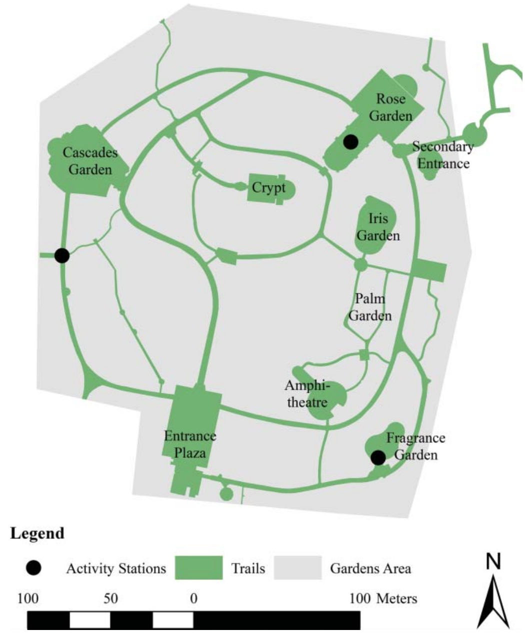

Figure 1 *Study area. (Color figure available online.)*

Sampling Procedure and Data Processing

The sampling itself took place during four days of the 2016 Passover vacation in Israel, a time used by many for travel and recreation activities,[2] meaning that the potential sample size increases during this period. Yet, the main reason for selecting this period was the possibility of taking advantage of an event occurring during this vacation (see the discussion of the experimental design).

Groups of day visitors were approached at the main entrance to the gardens and were asked to participate in the research in exchange for a small token. To control for previous knowledge, only unorganized groups in which none of the members visited the gardens in the previous twelve months were chosen to participate. Participants were handed a GPS logger, set to sample location every ten seconds, which they were asked to carry during their entire visit. After returning the logger, a questionnaire was administered. The first part was used to collect sociodemographic data and information on general visit patterns to nature sites, whereas in the second part, participants were asked to rate, on a seven-point Likert scale, the extent to which they have applied different behavioral strategies or were affected by certain factors in the current visit (see Table 1 for the statements and the variables representing them). A question regarding the extent to which participants used the map during the visit (on a five-point scale) was also included.

The GPS data were imported into ESRI's ArcGIS desktop environment (ESRI 2016) and their validity were visually assessed. A trajectory was considered valid if the entire sequence of visited trails could be identified with high certainty, partially valid if some uncertainty in location was evident yet most of the sequence could be identified, or invalid if large portions of the trajectory were missing or

Table 1 *Strategy- and influence-related statements and their complementing variables*

Statement	Variable
I've attempted to visit the entire gardens area	*S. Coverage*
I've preferred walking on central trails and avoid switching between trails	*S. Centrality*
I've chose to visit the trails in which I thought the vegetation and the scenery were likely to be the most beautiful	*S. Beauty*
I've taken the shortest path between the sites and activities I've wished to visit	*S. Shortest Route*
I've walked the trails that were the most adjacent to the various sites located within the Memorial Gardens	*S. Sites*
My decisions regarding where to spend my time during the visit were affected by other people traveling with me	*I. Group*
My decisions regarding where to spend my time during the visit were affected by the time I had allocated for the visit	*I. Time Budget*
Participating in the research affected my behavior	*I. Participation*
Carrying the tracking device during the visit affected my behavior	*I. Logger*

Note: The prefixes *S* and *I* indicate statements related, in accordance, to behavioral strategies and influencing factors.

the sequence of trails visited could not be identified clearly. The sequence of trails visited was recorded for all valid and partially valid trajectories, making the basic data set used for the analysis, along with the questionnaire data.

Experimental Design

To assess the influence of spatial layout and spatial cognition, two treatments were devised. First, the study took advantage of an event taking place during two of the four sampling days. As part of this butterfly-themed event,[3] new activity stations were placed within the gardens (see Figure 1). These additions, which operated during all activity hours, changed the spatial layout of the site by adding new spatial anchors.

The second treatment, which aimed to influence participants' cognitive spatial image of the site, included the design of two maps. The first one (i.e., the true map; Figure 2A) presented the trail network based on metric–Euclidean relationships. The second one (i.e., the simplified map; Figure 2B) presented a slightly distorted version of the first. These distortions mimicked known systematic biases[4] in spatial cognition in an attempt to minimize the known difference between cognitive images derived from maps and those derived from personal experience (Thorndyke and Hayes-Roth 1982; A. E. Richardson, Montello, and Hegarty 1999). Topological relationships within the trail network were stressed by depicting the most inner trails and the peripheral trails as complete circles, thus forming elements equivalent to Lynch's (1960) "paths." The entire site and the main attractions within it were aligned to the north–south and west–east axes, in accordance with the known alignment effect (Tversky 1981). The location of the Baron's crypt was enlarged and shifted to the intersection of these two axes, making it a more salient anchor point (Golledge 1978).

The two maps were distributed randomly to participants during all sampling days, meaning that two versions of each map were produced: one depicting the locations of the activity stations, distributed during event days, and one without them, distributed during nonevent days. Figure 2 presents the versions distributed during the event.

The binary nature of the two treatments and their combinations define four sampling groups (see Table 2). The true map–no event group was marked as the control group, because its experimental conditions included no intentional cognitive or spatial intervention (considering that the type of map or layout affects behavior). In accordance, its members' visit patterns were used as a baseline to which the experiment groups' patterns were compared.

Data

A total of 147 visitor groups were sampled, 115 (78.23 percent) of which had valid or partially valid trajectory data. These trajectories are not distributed evenly across sampling groups, with the event group underrepresented (Table 3). Crossing the trajectories data set with the questionnaires data further reduced sample size and increased the representation bias. In that context, it is important to notice that a rather strict definition of completeness and validity was used (see Table 3), meaning that sample sizes were larger when only a subset of the collected variables was used. Nevertheless, the available data certainly limit the analysis's depth, especially regarding statistical estimation. The analysis in the following section was carried out with these limitations in mind.

Results

Sample Characteristics and General Visit Patterns

As mentioned earlier, various variables were collected to characterize the participating groups. Table 4 summarizes their distribution for the participants with valid or partially valid trajectory data. Due to the size of the sample, most variables were transformed into binary variables. Logistic regressions were used to test whether the distribution of these variables varied between sampling groups and did not identify any significant effect (i.e., the null hypothesis that the distributions were the same could not be rejected).

The reported preferences regarding choice of behavioral strategies, on the other hand (Table 5), do show some variance. For instance, maximizing coverage was practiced to the greatest extent by members of the map group, walking central trails was most popular in the baseline group, and the shortest route strategy was preferred by members of the event group. Some differences can also be seen regarding external effects (Table 5), where the influence of members of the visiting group

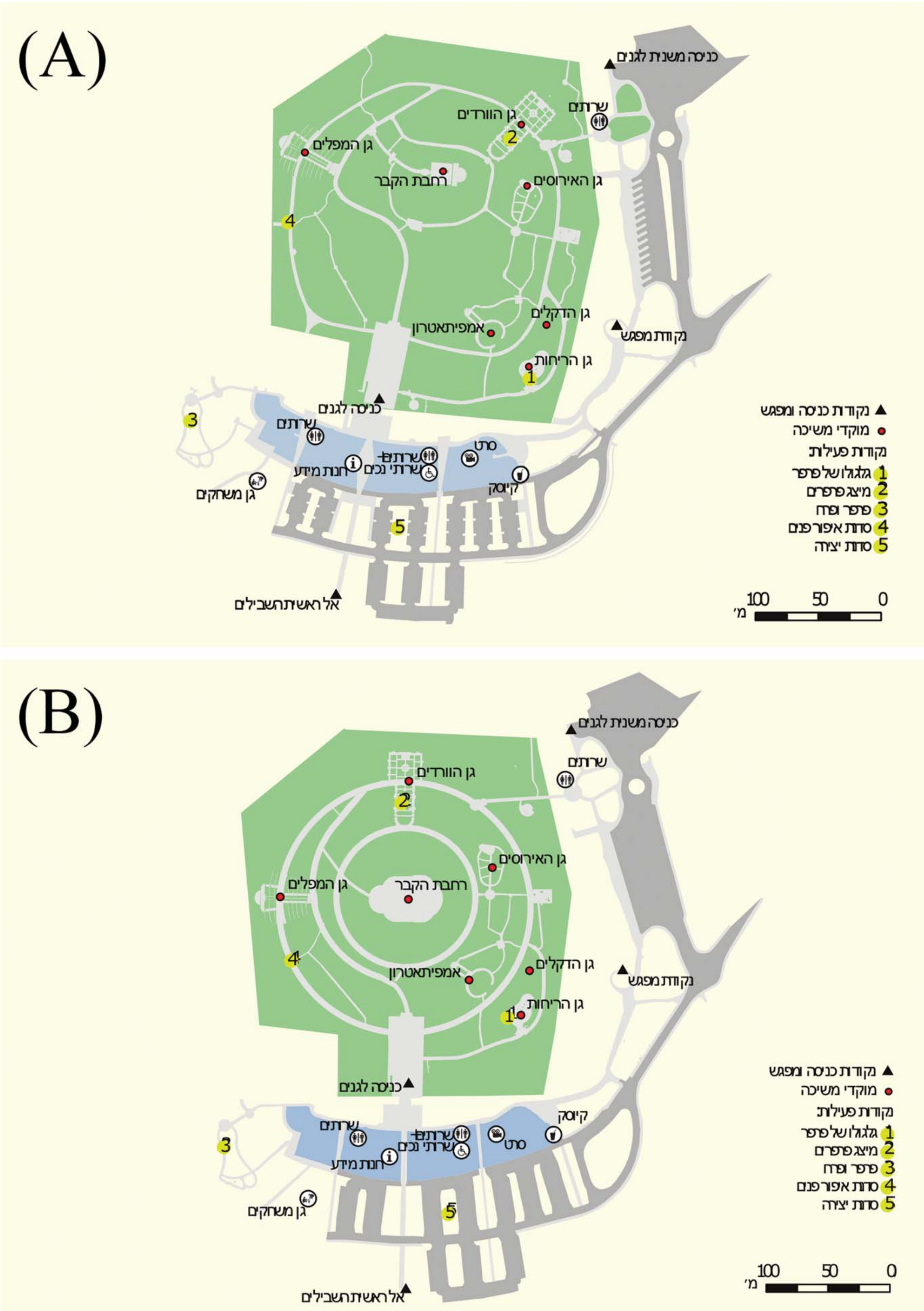

Figure 2 *Experiment maps: (A) True map, (B) simplified map. The figure presents the maps as they were distributed, thus featuring Hebrew writing. (Color figure available online.)*

Table 2 *Sampling groups by application of treatments*

		Time of visit	
		Not during event	**During event**
Map type	**True**	Baseline group	Event group
	Simplified	Map group	Event + map group

was mostly felt by members of the event and map sampling groups. Finally, it seems that the distributed maps were used to the greatest extent during the event. A one-way analysis of variance (ANOVA) reveals that only two of the previously mentioned differences are significant, the choice of *S. Coverage*, $F(98, 3) = 3.45, p = 0.02$, and the choice of *S. Shortest Route*, $F(99, 3) = 2.66, p = 0.05$.

It is probable that certain interdependencies exist within stated preferences of behavioral strategies (e.g., it is reasonable to assume that *S. Coverage* and *S. Centrality* contradict). In accordance, a principal component analysis was performed to identify broader behavioral tendencies. The resulting loading matrix (Table 6) suggests that the first two components, representing 54.96 percent of the variance, uncover such tendencies. The high and positive correlation of Component 1 with the *S. Centrality*, *S. Shortest Route*, and *S. Sites* variables suggests that this component reflects a focus on efficiently visiting sites and activities, in terms of time allocation. Component 2, on the other hand, is very highly and positively correlated with the *S. Coverage* variable and negatively correlated with *S. Shortest Route*, thus relating this component to a space-maximizing behavioral tendency. Hence, the subsequent analysis uses these components, labeled *S. Site* and *S. Area*, instead of individual strategy variables.

Influences on Stated Preferences

The variance evident in Table 5 suggests that even before affecting actual choices, the experimental treatments influenced participants' behavioral preferences, represented here by the behavioral strategy variables. To establish this argument, regression analyses were used to test the relation of strategy components to the independent variables presented in the previous section, excluding level of map usage (which is possibly dependent on the choice of behavioral strategy). Variables relating to external influences on behavior were transformed into binary variables.[5] Because the binary variables relating to participating in the research (*I. Participation* and *I. Logger*) were correlated, a new binary variable (*I. Research*) was formulated that received a value of 1 (i.e., true) if either of the previous variables was true and 0 (false) otherwise. In addition, dummy variables for type of map (*map*, true for the simplified map and false for the true map), time of visit (*event*, true for participants visiting during the event, false otherwise), and the combination of both (*second treatment*) were introduced to test the effect of the different treatments. The results of the two models, one for each strategy component, are presented in Table 7.

Overall, both models were significant—(1) $F(10, 75) = 2.61, p < 0.01$; (2) $F(10, 75) = 1.77, p = 0.08$—and the signs of the coefficients for individual-specific variables make general sense. For example, the presence of children and the influences of group members or time budget are all associated with an increased tendency toward site-oriented preferences. A significant experiment-related effect was, however, found only for the site-oriented strategy and only under the simplified map and combined treatments conditions. According to this, the event affects behavioral preferences only when combined with the simplified map, when it acts to neutralize its effect and encourages more time-efficient preferences. The second model identifies no significant effect for the treatments, suggesting that area-oriented behavioral preferences are more affected by predetermined factors, such as the group's character.

Effects on Overt Time–Space Behavior

Next, the effects of experimental treatments, along with other factors, on overt behavior were investigated. This was done by defining two overall measures of visit behaviors: percentage of visited trails (out of all trails; *coverage*) and the total visit duration (in minutes; *duration*). ANOVA tests have found a significant difference only for *coverage*, $F(92, 3) = 4.30, p < 0.01$, and not for *duration*, $F(92, 3) = 1.11, p = 0.35$, despite the average values of both varying across sampling groups (see Table 8).

Regression analyses were once again performed using the same variables as in the preceding section while also integrating the two strategy variables and a binary variable representing map usage levels (*map usage*, where the cutoff value for identifying high usage levels was 2). Again, both models were significant—(1) $F(13, 56) =$

Table 3 *Data validity by sampling group*

		Trajectory data quality			
Sampling group	***n* (percent of total)**	**Valid (percent of *n*)**	**Partially valid (percent of *n*)**	**Invalid (percent of *n*)**	**Valid trajectory data and complete questionnaire data (percent of *n*)**
Baseline	41 (37.89)	20 (48.78)	7 (17.07)	14 (34.15)	16 (39.02)
Event	32 (21.77)	20 (62.50)	4 (12.50)	8 (25.00)	17 (53.12)
Map	38 (25.85)	29 (76.32)	3 (7.89)	6 (15.79)	29 (76.32)
Event + map	36 (24.49)	27 (75.00)	5 (13.89)	4 (11.11)	20 (55.56)
Total	147 (100.00)	96 (65.31)	19 (12.92)	32 (21.77)	82 (55.78)

Table 4 *Sample characteristics for participants with valid or partially valid trajectory data*

Variable	Description	*n*	Value	Sample (percent of *n*)	Baseline (percent of group members)	Event (percent of group members)	Map (percent of group members)	Event + map (percent of group members)
Academic	Education level	98	Owns an academic degree	76 (77.55)	16 (76.19)	18 (81.82)	24 (77.42)	16 (75.00)
Visits	Number of yearly visits to nature sites	98	More than 5	38 (38.78)	7 (31.82)	11 (50.00)	12 (38.71)	8 (34.78)
First Visit	First-time visit to the Memorial Gardens	96	Yes	62 (64.58)	14 (63.64)	15 (71.43)	19 (61.29)	14 (63.64)
Children	Number of children (ages 0–12) in the visiting group	101	One or more	77 (76.24)	17 (77.27)	20 (90.01)	22 (68.75)	18 (72.00)

$2.62, p < 0.01$; (2) $F(13, 56) = 1.74, p = 0.08$—yet treatments showed significant effects only for the first model (see Table 9), suggesting that duration was related to other pregiven conditions (e.g., time budget and the presence of children). The positive and significant effect of area-oriented preferences on this variable seems to be more of a side effect of visiting more trails (as evident in Model 1) than a purposeful behavioral tendency of area-oriented visitors (i.e., Type I error).

The model for the coverage variable presents a couple of meaningful results. First, both behavioral strategies were found to have significant effects with the expected signs (minus for *S. Site* and plus for *S. Area*). Second, a significant effect was identified only for the type of cartographic representation (regardless of time of visit), which can be translated to an average increase of 3.78 in the number of visited trails (according to the coefficient's value, which represents a 7 percent increase). Because both the map and the combined treatment affect strategy-related preferences, however, it can be hypothesized that the effects of both treatments are underestimated here. In addition, this result suggests that the treatments affect overt behavior both directly and indirectly.

Spatial Patterns

To deepen the analysis of effects on overt behavior, changes in visitor flows were analyzed by trail and sampling group, using the high-resolution nature of the data. For this, changes in the share of participants visiting each trail (i.e., visit frequencies), relative to the baseline group, were computed and visualized (Figure 3). The average number of visits per participant was also calculated, as a measure that accounts for both overall frequency and the number of repeated visits. These visualizations expose a dominance of the peripheral trails in all scenarios (as evident in the average number of visits) but with some group-specific differences. The map group shows an increase in visit frequency for most trails, a result directly related to the increase in coverage identified earlier. Under the event conditions, however, only inner trails, especially those that connect activity stations, are more frequently visited. These patterns are almost entirely replicated under the event + map group conditions. Such patterns can assist in assessing the relative weight of each treatment: Although a clearer representation of topological relations can act to disperse activity, this effect does not appear to be strong enough to counter the converging effect of the anchors. If anything, convergence seems to intensify under the combined treatments conditions.

These overall patterns expose macrotrends of change. Yet trail-level changes in visit volumes could be the result of that trail becoming more attractive under experiment conditions (a direct effect) or of its neighborhood becoming so (an indirect effect). In the latter case, volumes in the neighborhood would change but transition probabilities from it to the

Table 5 *Mean and standard deviation of variables relating to behavior during the current visit*

Variable	*N*	Sample	Baseline	Event	Map	Event + map
S. Coverage	99	4.96 (1.66)	5.04 (1.69)	4.43 (1.78)	5.64 (1.25)	4.46 (1.77)
S. Centrality	100	4.35 (1.95)	5.04 (1.80)	4.33 (2.06)	4.16 (1.92)	3.96 (1.97)
S. Beauty	100	5.14 (1.73)	5.30 (1.94)	5.14 (1.71)	5.35 (1.49)	4.72 (1.84)
S. Shortest Route	100	3.17 (2.00)	3.00 (1.91)	3.90 (2.34)	2.48 (1.55)	3.56 (2.08)
S. Sites	100	4.17 (1.98)	4.74 (2.00)	4.00 (1.87)	3.61 (1.80)	4.48 (2.18)
I. Group	99	4.80 (2.22)	4.48 (2.63)	5.00 (2.43)	5.06 (1.65)	4.58 (2.34)
I. Time Budget	99	3.98 (2.23)	3.96 (2.22)	4.09 (2.57)	3.77 (2.20)	4.17 (2.08)
I. Participation	99	1.78 (1.48)	2.13 (2.03)	1.48 (1.08)	1.68 (1.16)	1.83 (1.55)
I. Logger	99	1.78 (1.63)	1.91 (1.93)	1.38 (0.92)	1.52 (1.31)	2.33 (2.06)
Level of Map Usage	101	3.29 (1.10)	3.26 (1.21)	3.81 (0.87)	3.06 (1.12)	3.19 (1.06)

Table 6 *Loading matrix for principal components*

	S. Site	S. Area
S. Coverage	−0.07	0.75
S. Centrality	0.52	0.26
S. Beauty	0.35	0.35
S. Shortest Route	0.59	−0.47
S. Sites	0.51	0.14
Cumulative variance	0.28	0.55

specific trail would remain the same, whereas in the first a change in probabilities would be registered. To identify trails that truly became more or less attractive, trail-level visit volumes were defined to be the result of multiplying transition probabilities with visit volumes on adjacent trails (Equation 1). A measure for direct effect was then developed using a simple manipulation (Equation 2), adding and subtracting the baseline group's transition probabilities (these cancel each other out and thus do not change results). Rearranging (Equation 3), two components can be identified, the first representing expected volume on a trail under baseline conditions and actually recorded visit volumes on surrounding trails (indirect effect) and the other depicting the deviation from this expectation, thus quantifying the direct effect.

$$V_{x,c} = \sum_{y \in Y} \mathrm{Pr}_{y \to x,c} V_{y,c} \tag{1}$$

$$V_{x,c} = \sum_{y \in Y} \left(\mathrm{Pr}_{y \to x,c'} + \mathrm{Pr}_{y \to x,c_0} - \mathrm{Pr}_{y \to x,c_0} \right) V_{y,c'} \tag{2}$$

$$V_{x,c} = \sum_{y \in Y} \mathrm{Pr}_{y \to x,c_0} V_{y,c'} + \left(\mathrm{Pr}_{y \to x,c'} - \mathrm{Pr}_{y \to x,c_0} \right) V_{y,c'} = \sum_{y \in Y} \mathrm{Pr}_{y \to x,c_0} V_{y,c'} + \Delta_{\mathrm{Pr}} V_{y,c'}, \tag{3}$$

where $V_{x,c}$ is the volume of visits on trail x under conditions c, Y is the set of trails adjacent to trail x, $\mathrm{Pr}_{y \to x,c}$ is the transition probability from trail y to trail x under conditions c, c_0 signifies baseline conditions, and c' signifies one of the experiment conditions.

Table 8 *Averages and standard deviations for coverage (percentage) and duration (minutes) variables, by sampling group*

Sampling group	Coverage		Duration	
	M	*SD*	*M*	*SD*
Baseline	0.34	0.10	52.04	23.81
Event	0.34	0.12	61.81	19.52
Map	0.41	0.09	53.51	21.59
Map + event	0.31	0.14	60.81	24.61
All participants	0.35	0.12	56.99	22.60

Figure 4 presents the spatial distribution of direct effects by sampling group. Only minor differences from overall effects (Figure 3) are evident under the event conditions: a positive, instead of negative, effect near the southeastern anchors and the absence of a positive effect on peripheral trails. Inspecting the distributions of overall and direct effects for the other groups, however, exposes much discrepancy: The overall positive effects registered under map conditions become constrained mostly to the inner trails, whereas the opposite picture is evident for the event + map group, where positive effects are evident also for the outer trails. When interpreting these results, it is important to keep in mind that the event treatment affected the entire visitor population, whereas the map treatment affected just participants. Thus, it is not easy to deduce whether effects identified under event conditions represent the anchors' effect or a response to changing behavioral patterns.[6]

Interestingly, the combination of both treatments increased the attractiveness of outer trails, an effect that was not evident for other groups, pointing to the combined effect being more than the sum of the two distinct effects. A combined attentional effect might

Table 7 *Results for the (1) S. Site and (2) S. Area models*

Variable	Model 1	Model 2
Academic	−0.46	−0.16
Visits	0.65**	0.07
First Visit	0.09	−0.42
Children	0.36	−0.54*
I. Group (binary)	0.30	0.27
I. Time Budget (binary)	0.39	0.10
I. Research	0.35	−0.10
Map	−0.80**	0.12
Event	−0.33	−0.53
Second Treatment	0.90*	−0.11
N	86	86
R^2	0.26	0.19

*$p < 0.1$.
**$p < 0.05$.

Table 9 *Results for the (1) Coverage and (2) Duration models*

Variable	Model 1	Model 2
Academic	−0.02	−1.99
Visits	0.02	10.68*
First Visit	0.04	10.01*
Children	0.01	14.42**
I. Group (binary)	−0.04	4.53
I. Time Budget (binary)	−0.07**	−12.43**
I. Research	0.02	0.13
Map	0.07*	3.00
Event	0.02	8.63
Second Treatment	−0.05	−3.23
S. Site	−0.02*	−2.69
S. Area	0.04***	4.54**
Map Usage	0.04	7.24
N	70	70
R^2	0.39	0.28

*$p < 0.1$.
**$p < 0.05$.
***$p < 0.01$.

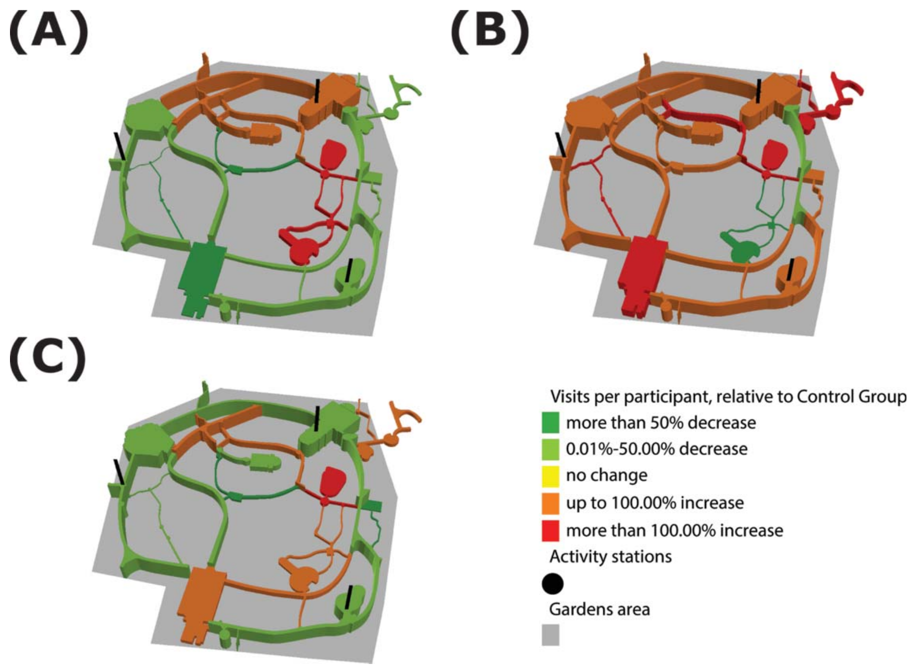

Figure 3 *Change in visit frequencies relative to baseline group frequencies for (A) event group, (B) map group, and (C) event + map group. Height represents average number of visits per participant. (Color figure available online.)*

be at work here: The simplified cartographic design draws attention to the peripheral trails as a distinct system within the site and the new activity anchors, by their location on it, make it more salient cognitively. Although these effects might seem quite marginal in relation to the total volume of visits, when aggregated over the entire population, they could produce an effect that is worth considering.

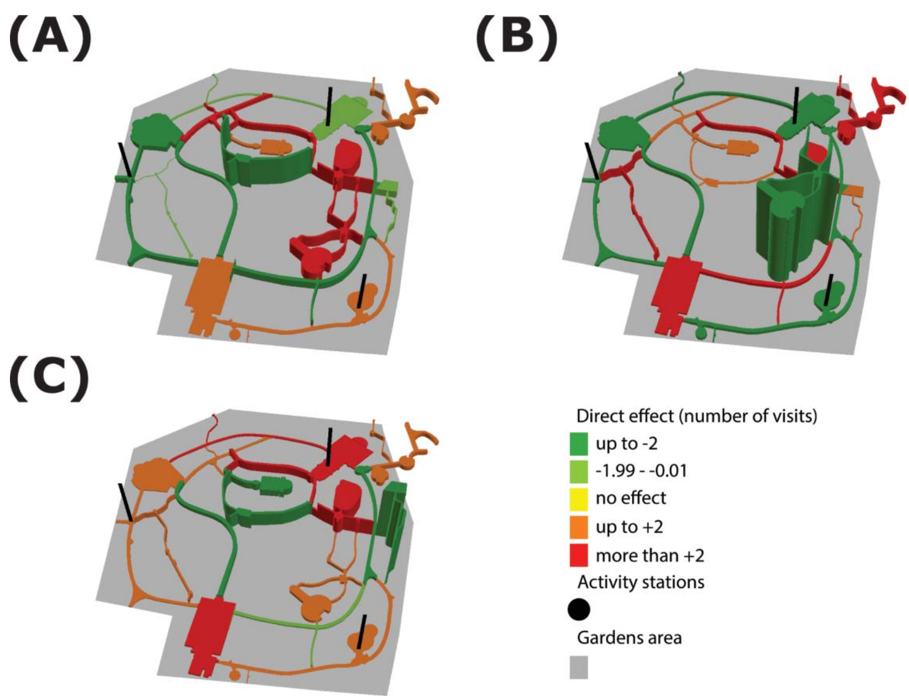

Figure 4 *Direct effect of treatments by trail for (A) event group, (B) map group, and (C) event + map group. Height indicates the relative weight of the direct effect out of the total effect (where absolute values were used to avoid negative heights). (Color figure available online.)*

Discussion and Conclusions

A common conceptualization of the decision-making process behind time–space activity patterns is a procedural–sequential one (e.g., Golledge and Stimson 1997; Gärling and Golledge 2000; Hannes, Janssens, and Wets 2008, 2009; and to a certain extent, also the time–geographic model). Yet, the relative weight of each factor in the process is rarely discussed, leaving an open gap between the physical and the abstract within the study of spatial behavior (Couclelis 2009; McCormack and Schwanen 2011; Lindelöw et al. 2014; Kwan and Schwanen 2016). Characterizing the relative influence of each is important, especially if one wishes to analyze the extent to which time–space behavior is the result of volitional control. The findings of this research produce new insights in this context, because they shed light on the interactions between spatial layout, activity anchors, spatial cognition, and preferences and the relative weights of each of these factors.

The peripheral path remaining the most frequently visited one over all experiment groups suggests that the initial spatial layout is the element that affected visit patterns to the greatest extent. Because this effect might have been driven by the location of most attractions near this path, it is probably not only physical, relating to how layouts constrain behavior, but is also of a cognitive or precognitive nature. The effects of all other components seem, however, to be interdependent. Even preferences, which hold a direct influence on behavior (where coverage increases with *S. Area* and diminishes with *S. Site*), were influenced by treatments: The restrictive site-oriented strategy was less practiced when the topological structure was presented with more clarity by the simplified map, unless combined with the anchors treatment, which acted to highlight participation in activities as the visit's objective on expanse of sightseeing. The two treatments also interacted in directly affecting trail-level visit frequencies. Although each treatment holds its own effect, with the activity anchors influencing distance estimations by segmenting the peripheral path and the simplified map highlighting distinct paths and the nodes of transition between them, their combination has led to a new effect, as discussed in the previous section.

These findings thus draw a picture in which the general spatial layout creates an initial effect that sets the boundaries for the influences of other components. These influences are interdependent, thus making any differentiation between the effects of the various factors artificial in nature, given that all actions rely on some form of a cognitive spatial representation relating to anchors (or their absence). This picture also exposes the weight of conscious decision-making procedures in the formation of time–space behaviors; preferences, the only volitional element, rely in some way on all of the other components that were studied here. The critique on the assumption of volitional control is thus validated, showing that conscious decisions cannot be studied without considering the external and internal conditions shaping them.

These relationships could have been further explored using structural equation models, a popular and useful tool in studying such interdependencies (Gärling and Golledge 2000), yet applying those using small and unevenly distributed samples is problematic. Another limitation of the current analysis is the location of the event-related activity stations on the dominant peripheral trails, which might have constrained these anchors' influence. It is probable that locating them on the less visited inner trails would have produced a greater change. Moreover, it is possible that the hierarchy evident here is the result of the specific situation and that in everyday situations it would change (although it is reasonable to assume that in such situations the influence of external conditions would only intensify). Finally, by focusing on spatial structure and cognitive image, the research here does little to consider other aspects of the decision-making procedure, such as the emotional and affectual dimensions (Anderson and Smith 2001) or the effects of group dynamics and distributed cognition on map-reading and navigation tasks (Laurier and Brown 2008). Some of the results here could be interpreted along these dimensions; for example, attributing spatial layout's effect to the affectual dimension of design (Kraftl and Adey 2008) or interpreting the effects of the event as emerging from a response to macrolevel dynamics. Yet, it would be more advised to face these limitations by using dedicated research designs, by using larger samples and applying structural equation estimation techniques to them, or by inspecting behavior under differing spatial and activity contexts.

Nevertheless, and despite these limitations, this study, by using high-resolution mobility data within a dedicated experimental design, offers more than an initial answer to the question of the role of volitional control within time–space activity. This answer forms a conceptual foundation that could enable the further evolvement of time–space behavioral studies and, thus, it is hoped, would lead the way toward more complex, deep, and comprehensive understanding of this behavior. ■

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Notes

[1] The Baron was a key figure in the development of the modern Jewish settlement in Israel during the nineteenth century.

[2] The sampling was carried out during the secular part of the Passover vacation (known as *Chol Hamoed*) in which the mobility of more religious Jews is not constrained by religious traditions.

[3] During this time of year, the blossoming vegetation within the gardens attracts many migrating butterflies.

[4] In contrast with highly simplified maps that are more commonly used (e.g., Guo 2011).

[5] *I. Group* and *I. Time Budget* were labeled true for values above 3; the cutoff value used for the *I. Participation* and *I. Logger* variables was 1.

[6] This latter explanation can be supported by the fact that no significant influence on stated preferences was found for the event treatment (see Table 7).

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