Wayfinding Decision Situations: A Conceptual Model and Evaluation

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Abstract. Humans engage in wayfinding many times a day. We try to find our way in urban environments when walking towards our work places or when visiting a city as tourists. In order to reach the targeted destination, we have to make a series of wayfinding decisions of varying complexity. Previous research has focused on classifying the complexity of these wayfinding decisions, primarily looking at the complexity of the decision point itself (e.g., the number of possible routes or branches). In this paper, we proceed one step further by incorporating the user, instructions, and environmental factors into a model that assesses the complexity of a wayfinding decision. We constructed and evaluated three models using data collected from an outdoor wayfinding study. Our results suggest that additional factors approximate the complexity of a wayfinding decision better than the simple model using only the number of branches as a criterion.

1 Introduction

Successful wayfinding (i.e., our ability to find a distal destination from some origin; [23]) depends on several factors, including the complexity of the environment in which wayfinding occurs. The layout of an environment influences the ease with which a corresponding mental representation is formed [5,32]. In addition, familiarity with and structure of the environment help determine which strategies are used to find the way [7,14].

During wayfinding, the layout of the path network (e.g., the street network of an outdoor environment) is of particular importance. In these networks, path segments (the streets) meet at intersections where wayfinding decisions must be made. Accordingly, these intersections and their configuration are a main contributor to route complexity. In the dynamic context of wayfinding, they are often referred to as decision points (e.g., [16]).

One simple measure for establishing a decision point's complexity is the InterConnection Density (ICD; [24]). The ICD of a network is the average number of path segments meeting at an intersection. In other words, in O'Neill's terms, the complexity of a decision point is determined by the number of options to continue one's way.

However, this measure ignores certain dynamics of wayfinding [16]. For example, continuing straight at an intersection is arguably easier than turning left or right. These dynamics are reflected in Mark's measure of route complexity [21]. In this measure,

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slot values are attributed to wayfinding situations, depending on the complexity of an intersection (e.g., whether the intersection is a T-intersection or the convergence of six different streets) and the corresponding, possible actions (e.g., continuing straight or turning left). Higher slot values denote higher complexity.

Ambiguity in the decision situation also needs to be considered. For example, executing the instruction "turn left" becomes more complex when there are several options to turn left compared to when there is only one path segment heading in that direction [11]. Landmarks may help to reduce ambiguity (and thus complexity). References to salient geographic objects (e.g., "turn left at the post office") anchor actions in space [4]. They signal crucial actions to perform and support identifying the right spot at which to perform them [20].

During route following (i.e., instructed wayfinding) the interplay between instructions and environment also become important. Good instructions may ease wayfinding considerably even in highly complex environments; bad instructions on the other hand may make wayfinding nearly impossible even in simple environments [28].

Overall, wayfinding constitutes a dynamic decision-making process during which people have to make decisions on the spot. Temporal constraints depend on the mode of travel; for example, pedestrians usually have more time during spatio-temporal decision situations than car drivers. There has still been little research about how mobile, location-based decision-making is different from other types of decision-making. General decision theory covers a wide range of models with different foci such as describing how decisions could or should be made or specifying the decisions that are made [9]. In the cognitive literature, behavioral decision theory has been emphasized because human decision-making is not optimized in a strictly mathematical and economical sense [29].

Mobile, location-based decision-making involves spatio-temporal constraints that relate not only to people's behavior in large-scale space [17], but also to their interaction with mobile devices and the environment, and perceptual, cognitive, and social processes. This involves multiple psychologies of space [22] and different time scales [6]. Special tools have been developed for studying the interaction between individuals, environments, and mobile devices [19].

Mobile devices have the general challenge of presenting information to people on the move. Despite their technological limitations (e.g., a small screen size), users can reduce the complexity of a spatio-temporal decision situation by off-loading what would otherwise be cognitive work (e.g., [3]). "Cognitive work" in this context refers to the effortful processing that often accompanies explicit decision-making. People can off-load cognitive work onto the environment during wayfinding by, for example, referring to a digital map. Accordingly, the cognitive load theory (CLT; [2]) offers a way of assessing and affecting some critical components during the design process of digital maps.

Adaptive location-based services (LBS) change the presentation of the map, or of the wayfinding instructions in general, depending on the current context, a user model, and a task model [25]. A large number of factors can be considered as context relevant for adaptive LBS, including position, time, speed, means of transportation, or weather information [27].

Cognitive off-loading depends on the interactions between each individual's cognitive abilities, the task at hand, and the immediate environment. During wayfinding, spatial abilities become especially critical [1]. Spatial abilities may vary according to age, gender, working memory capacity, reasoning strategies, preferred learning styles, attitudinal differences, and so forth [34]. One way of predicting wayfinding performance, specifically, is through a participant's self-reported sense of direction. For example, Hegarty and colleagues [12] found that participants' scores on the Santa Barbara Sense of Direction Scale (SBSODS) were more related to tasks that required updating over self-motion than those that required learning spatial information second-hand (e.g., as from a physical map).

In this paper, we propose a model for the complexity of pedestrian wayfinding decision situations in street networks. Our model describes the complexity of a decision situation with three elements: an *environmental model*, *a user model*, and an *instruction model*. We argue that a combination of these three elements is better suited for describing the complexity of a wayfinding decision situation than any single element or any combination of two of them. Three models are evaluated in terms of the above-mentioned factors. This evaluation demonstrated that models incorporating these factors are able to capture the complexity of a wayfinding decision situation better than a simple model using only the number of branches. Our dependent measures included the duration of making wayfinding decisions, the number of head movements, the number of gaze switches from the environment to the map, and the total time spent on the map. These measures can serve as an indication of cognitive load.

A context-aware pedestrian wayfinding assistant could use our model to minimize the complexity of the decision situations its user will be facing along the route. The route-planning algorithm would consider the complexity of each node in the street network for the given user, instead of choosing a user-independent route that is only optimized by environmental factors. The wayfinding assistant could also consider several possible route instructions for each decision point and choose the least complex one for the given user.

In section 2, we define the term *wayfinding decision situation* and introduce a conceptual model to describe its complexity. Section 3 introduces the wayfinding study used to evaluate three operational models. In section 4, we present the results of this evaluation, and in section 5, we discuss their implications for future research and LBS design.

2 Wayfinding Decision Situation

Wayfinders utilize environmental information, instructions (e.g., verbal or pictorial) and their spatial and cognitive abilities in order to make wayfinding decisions [23]. The complexity of these decisions is characterized by the structure of the given environment, the goals and task of the wayfinder, as well as her own characteristics. Thus, taking only environmental aspects into account, such as the number of branches at a decision point (as in the ICD model), is rather limited. For instance, a decision point with six branches can be less complex for a wayfinder than one with four branches if the given instructions for the former decision point are less complex. It is even possible that the same decision point is less complex for one wayfinder than for another because of their individual differences and spatial abilities. We propose a model that incorporates environmental, instruction, and user factors in order to characterize the complexity of wayfinding decisions and define it as wayfinding decision situation:

"A wayfinding decision situation occurs when a specific wayfinder has to make a wayfinding decision in a certain environment with a certain instruction."

In the following, we provide a conceptual model that describes the complexity of wayfinding decision situations and then evaluate three operational models.

2.1 Conceptual Model

The conceptual model is composed of environmental, instruction and user factors (see Figure 1) and aims at describing the factors that influence the complexity of wayfinding decision situations. The proposed conceptual model integrates several factors that can have an impact on the complexity of wayfinding decision situations but raises no claim to completeness.

Environmental Model. The environmental information that is available to a wayfinder, such as the geometry of a decision point, is crucial for making wayfinding decisions. The number of branches at a decision point is often used as a criterion for complexity [24]. Obviously, as the number of wayfinding options increases, the complexity of a decision point also increases. Landmarks are an important factor of the environmental context and are often used in navigation instructions [26]. Architectural differentiation [31], the availability of objects in the environment identifiable as landmarks, the unambiguity and saliency of landmarks, and their advance visibility [33] can have an impact on the complexity of a decision point. Even a decision point with only three branches may become extremely complex if the environmental cues cannot optimally be utilized by the user. Environmental factors that have an impact on the complexity of wayfinding decision situations can be classified into two categories. The first category contains all factors that contribute to complexity independent of the instructions (e.g., the number of branches, the geometry of an intersection). The factors that become (mostly) important through their use in an instruction, such as environmental landmarks, constitute the second category. The set $E = \{(c_1, f_1), (c_1, f_2), ..., (c_2, f_n)\}$ is comprised of all environmental factors that can influence a wayfinding decision situation as well as their corresponding category c_i. More than one element of this set can coexist in a given wayfinding decision situation, thus having a weighted additive linking. Environmental complexity $c(e), e \subseteq E$, is computed based on the existing environmental factors at the given decision point and a weight function w_E defines the impact of each factor on complexity.

Instructions Model. To reach a goal (e.g., while walking from a starting point A to a destination B), wayfinders have to perform different activities and interact with the environment in order to make several wayfinding decisions. Wayfinders use aids (e.g.,

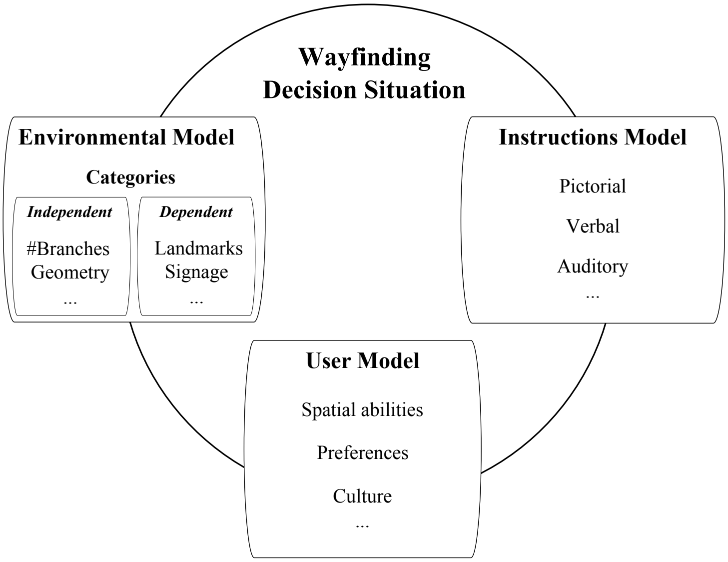

Fig. 1. The figure depicts a wayfinding decision situation. The environmental, instruction and user factors of the wayfinding decision situation model are used to assess its complexity.

maps; verbal, auditory and pictorial instructions; knowledge provided by other humans; [30]) to make wayfinding decision situations less complex. These aids help us fulfill our tasks when cruising in unfamiliar environments or when looking for a hospital. The complexity of an instruction is strongly related to the represented environmental factors. For instance, the complexity of landmark based instructions is related to the saliency and the advance visibility [33] of the incorporated landmarks (among other factors). An instruction, apart from being a wayfinding aid, can also have a negative effect on the complexity of a decision situation if its complexity is high. Thus, instructions are an important factor to be considered in wayfinding decision situations. The set $I = \{t_1, t_2, ..., t_n\}$ contains all the different instruction types. In contrast to the environmental model, in a given decision situation, only one instruction type can be active. Combinations of instruction types, such as the combination of verbal and pictorial instructions, form an additional instruction type. The complexity of the instructions $c(t_i), t_i \in I$, strongly depends on the instruction type (e.g., landmark based instructions); therefore, it is necessary that measures for assessing the complexity are type-specific (e.g., landmark based measures). A weight function w_I defines the impact of the type-specific measures on the instruction complexity.

User Model. A wayfinding decision situation differs for every wayfinder. Individuals' spatial abilities, preferences, interests, general knowledge, and cultural background have an impact on decision making during wayfinding [10]. It is more likely that a wayfinder with high spatial abilities will be able to process the environmental information and decrypt instructions faster than a wayfinder with low spatial abilities.

A wayfinder with better problem solving abilities is able to process environmental information more easily. For example, she may be able to incorporate the slope of the branches at an intersection as a criterion when it comes to finding the way to an orthopedics by making the inference that a place like that would be easily accessible and not on the top of a hill. The set $U = \{f_1, f_2, ..., f_n\}$ contains all factors representing the user characteristics that can have an impact on complexity and the function $f(U)$ represents the link between these factors. The user factors always coexist in a wayfinding decision situation and a weight function w_U defines the importance of the given factors.

Our proposed conceptual model takes into account the factors mentioned above and can be summarized as $c(e, t_i, U) = c(e) \oplus c(t_i) \oplus f(U)$, where $c(e), e \subseteq E$ is the resulting environmental complexity, $c(t_i), t_i \in I$ the complexity of the instructions, and $f(U)$ are the user factors that can account for more or less complexity of the wayfinding decision situation. The operator $\oplus$ represents a linking between the factors.

2.2 Operational Model

A model that describes the complexity of a wayfinding decision situation will have a significant impact on several aspects of wayfinding assistance. As a first step towards an operational model, we use a subset of the factors introduced in the conceptual model to construct three models. We then compare them to a widely used model that incorporates only the number of branches at a decision point [24].

$$\textit{Branches Model} = \textit{number of branches} \tag{0}$$

Each model introduced below is a step-wise extension of the previous, starting with the simple model (0) that uses only the number of branches as a complexity measure. The conceptual model $c(e, t_i, U)$ allows for incorporating a whole range of factors (as any context model's instantiations will necessarily always be incomplete). We will test the models against data collected in a human participants study. Therefore, we only incorporate factors in the operational models that correspond to data provided by the experiment. For this reason, the instruction type t_i used for the operational models is equal to pictorial landmark-based instructions, the user factors U are limited to the values obtained through the Santa Barbara Sense of Direction Scale (SBSODS) [12], and the environmental factors $e \subseteq E$ are limited to the number of branches at a decision point.

Incorporating Environmental and Instruction Factors. In a first step, we incorporate only the environmental factor, namely the number of branches $\subseteq E$ and the pictorial landmark-based instructions $\in I$:

$$c(e, t_i) = c(e) \oplus c(t_i) \Longrightarrow$$

$$c(e, t_i) = (1 - w_1) * \#br + w_1 * (\beta * adv_{vis} + (1 - \beta) * lm) \tag{1}$$

#br: number of branches, adv_{vis}*: advance visibility and lm:* $landmark_{matching}$

$c(e, t_i) \in [0, 1], e \subseteq E, t_i \in I$

The first part of the model describes the environmental complexity as the number of branches at the decision point where a wayfinding decision situation occurs. The second part of the model defines the complexity of the instructions and is computed as the weighted addition of the advance visibility adv_{vis} [33] of the landmarks used in the given instruction and the landmark matching $landmark_{matching}$ value. The landmark matching value is represented as the ease with which the pictorial representations of landmarks can be matched with images of the corresponding real landmark. The advance visibility measure was introduced by Winter [33] and classifies landmarks based on how salient they are and how early they are visible on a path segment towards a decision point. The values for landmark matching were retrieved through an experiment described in section 3.2.

Incorporating the User. In a second step, we extend the model by incorporating user characteristics. We use the SBSODS score as a value for the weight w_1 introduced in the previous model (1). The underlying assumption for this step is that users with higher spatial abilities would be affected more by the complexity of the instructions, rather than by the complexity of the environment.

$$c(e, t_i, U) = c(e) \oplus c(t_i) \oplus f(U) \Longrightarrow$$

$$c(e, t_i, U) = (1 - sa) * \#br + sa * (\beta * adv_{vis} + (1 - \beta) * lm) \tag{2}$$

sa: SBSODS, #br: number of branches, adv_{vis}*: advance visibility and lm:* $landmark_{matching}$

$$c(e, t_i, U) \in [0, 1], e \subseteq E, t_i \in I$$

We also introduce a third model that incorporates the user factors using an additive linking.

$$c(e, t_i, U) = c(e) \oplus c(t_i) \oplus f(U) \Longrightarrow$$

$$c(e, t_i, U) = w_1 * \#br + w_2 * (\beta * adv_{vis} + (1 - \beta) * lm) + w_3 * sa \tag{3}$$

sa: SBSODS, #br: number of branches, adv_{vis}*: advance visibility and lm:* $landmark_{matching}$

$$c(e, t_i, U) \in [0, 1], e \subseteq E, t_i \in I$$

The weights w_1, w_2, and w_3 are constrained to sum up to one. The weight β, as well as the values for adv_{vis}, lm and #br are within 0 and 1.

In the following, all three models will be evaluated with regard to how well they fit the data collected during an outdoor wayfinding study. All the weights of the introduced models were estimated using a genetic algorithm that is discussed in section 4. The factors used in the models were normalized using the maximum values obtained in two experiments (discussed in section 3). The normalized values from the SBSODS were inverted, with a higher value denoting lower spatial abilities (since a higher score of the model denotes higher complexity).

3 Experiments

In the following we report on two experiments that were conducted in order to collect the data necessary for the evaluation of the operational models.

3.1 Outdoor Wayfinding Experiment

An outdoor wayfinding experiment was conducted in the city of Zurich and constituted one task of a larger study [15]. The data collected from this experiment were used to fit the operational models introduced in section 2.2.

Participants. We recruited 14 participants for the wayfinding experiment. Each participant was provided a small monetary compensation for his/her participation. All participants were recruited through collaboration with a nearby hostel and were unfamiliar with the city of Zurich. Due to errors in the recording software, three data sets were lost. The remaining 11 participants (seven females) had an average age of 26.8 years (min 21, max 50, SD 8.3). They had different cultural backgrounds, none of them was a geographer or cartographer, and none of them was using maps in their profession.

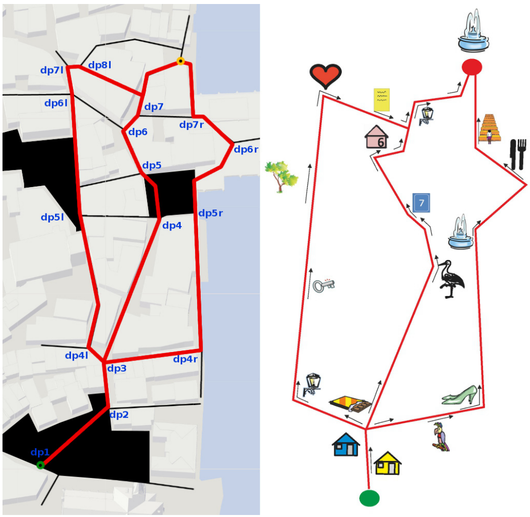

Fig. 2. The left side of the figure illustrates the area of the experiment and the decision points of the three routes. The pictorial map on the right was given to the participants.

Experiment Set-up and Procedure. The experiment took place on the streets of the old town part of Zurich (see Figure 2, left), where no cars are allowed. At the starting position, participants were given the task on a 28 × 28 cm paper print ("On this map you can see three possible routes that lead from your current position (green point at the bottom) to the next goal (red point at the top). Please make your way to the goal").

They had to reach a destination marked on the map with a red dot (see Figure 2, right) printed on the back side of the paper. This abstract map illustrated three routes that could be chosen in order to reach the destination as well as icons representing landmarks in the environment (i.e., buildings, signs) as a wayfinding aid.

The participants were equipped with a mobile eye tracking system[1] and had to carry a backpack ($\sim$ 2 kg) with the accompanying eye tracking hardware. They were not allowed to interact with other people or with the experimenters. The experiment ended either when the participants reached and correctly identified the destination or when they gave up.

During wayfinding, we tracked the eye movements of each participant and their field of view as recorded through the front camera of the eye tracker. We used these data in order to extract additional measures: number of head movements, number of gaze switches from the environment to the map, total time of map usage, and time spent in a wayfinding decision situation.

Data Post Processing. It was necessary to validate the captured eye tracking data because of possible distortions due to changing light conditions. We manually analyzed each frame of the captured eye movements in order to validate pupil detection and manually corrected frames where the pupil was not correctly detected. The validation and correction procedure can be manually achieved using the software[2] provided by the eye tracking vendor.

Extraction of Measures. Two human raters qualitatively analyzed the captured video frames (field camera) as well as the eye movements in order to perform a segmentation of each wayfinding trial and define the start and end point of every wayfinding decision situation. A wayfinding decision situation started immediately after the end of a previous one and ended when the participant had decided and was heading towards one of the available branches of the decision point. Overall, 75 decision situations were identified.

For each of these segments, we registered its duration (time to make a decision) as well as the number of head movements (change of the field of view), based on a manual analysis of the video frames of the field camera. Moreover, we used the captured eye movements to register the gaze switches from the environment to the map as well as to compute the total duration of map usage. These measures were separately used in the evaluation to estimate the fit of the operational models. Monocular eye trackers, such as the one used in our study, suffer from the parallax error [13]. They can be calibrated only for one distance at a time. Due to varying distances between the participant and the objects in the environment, we could not use the gazes in the environment, for example, to extract measures based on the gazes towards landmarks.

The advance visibility used to assess the complexity of the instructions was computed based on the values gathered from an analysis of the experiment area. We used a 3D model of the area in a GIS software[3] and computed the isovists for every landmark used in the instructions as well as the intersection of each isovist with the corresponding route segment towards the decision point.

[1] Dikablis - `www.ergoneers.com`
[2] Ergoneers - DLab Analysis.
[3] ArcGIS 10.1.

3.2 Web Experiment for Landmark Identification

We performed a web experiment for the evaluation of the selected map icons that served as landmark representations. The collected data were used to score the map icons based on how well they represented the real landmarks in the environment. These data were used for the computation of instruction complexity ($landmark_{matching}$).

Experiment Set-up and Procedure. The web experiment was implemented using JavaScript. The first page contained a task description and an example illustrating the task. When the participants started the actual experiment, they were directed to a website displaying one image of the real environment and the corresponding map icon. Participants were then instructed to click as fast as possible on the position of the real-world image (i.e., where they thought the corresponding landmark was located). After each click was performed, the next image and map icon were shown.

In total, seventy-two participants around the world took part in the experiment. The images and their corresponding map icons were randomly ordered for each participant. We registered the time needed to decide and click on the image, as well as whether the map icon was matched correctly.

The average time needed to perform a correct match was used for ranking the 16 map icons. A linear regression revealed a significant positive correlation of the ranking with the total number of errors that occurred for each map icon ($R^2 = .475, p < .010$).

4 Results

The data collected from the experiments were normalized using their maximum values and used to estimate the parameters (weights) of the models. The best-fitting parameter for the 1-parameter model (2) was determined through a brute-force search. The best-fitting parameters for the two- (1) and four-parameter models (3) were determined through a genetic algorithm.

4.1 Parameter Estimation Algorithm

A custom-written genetic algorithm was used in order to estimate the values of all parameters. Using this algorithm, we attempted to find the minimum summed and squared error (SSE) between the observed values of each dependent variable (i.e., decision time, time on map, map switches, and head movements, separately) and the values predicted by two- (1) and four-parameter models (3). Observed values were not aggregated over decision point or participant; thus, the genetic algorithm was used to fit 75 values. The algorithm started with 1000 randomly generated combinations of parameter values (i.e., “organisms”). The starting values for all parameters were constrained to fall between 0 and 1. Each iteration of the genetic algorithm consisted of three steps: selection, reproduction, and mutation. During selection, the best-fitting of every eight organisms was chosen for reproduction (i.e., “tournament selection”; [8]). During reproduction, the organisms were randomly paired and converted to bits, a random crossover point was determined, and every pair of organisms exchanged bits below that crossover point.

During mutation, every bit of every organism had a 0.5% chance of changing from a zero to a one or vice versa. Each parameter was represented by 17 bits, corresponding to a precision of approximately ±0.0001. The best-fitting organism over 100 iterations was maintained and ultimately used to evaluate each model. In order to compare models with different numbers of freely varying parameters, SSE for each model was converted to Bayes' information criterion (BIC; [18]).

The reliability of the genetic algorithm was validated by estimating known parameter values for both two-parameter (1) and four-parameter models (3). These initial parameter values were randomly generated using each model's constants (i.e., number of branches, advance visibility, landmark matching, and SBSODS score). Each parameter was constrained to fall between 0 and 1. For the four-parameter model (3), w_1, w_2, and w_3 were constrained to sum to one. Standardized decision times were generated using these initial parameter values and the constants for each combination of decision point and participant. The genetic algorithm was then used to estimate the initial, randomly generated, parameter estimates. This validation procedure was repeated 100 times. Variability and skew in the distribution of the differences between estimated and initial parameter values were used to evaluate the genetic algorithm's performance for each model.

4.2 Validation Results

In general, the validation procedure suggested that the genetic algorithm performed excellently for both models. For the two-parameter model (1), variance in the distributions of the differences between estimated and initial parameter values was 0.0000001 and 0.0000091 for w_1 and β, respectively; skew in the distributions of the differences between estimated and initial parameter values was -0.13 and -6.37 for w_1 and β, respectively. Because of the extreme precision with which β was estimated, this amount of skew is negligible (though perhaps notable). For the four-parameter model (3), variance in the distributions of the differences between estimated and initial parameter values was 0.0103, 0.0084, 0.0388, and 0.0701 for w_1, w_2, w_3, and β, respectively; skew in the distributions of the differences between estimated and initial parameter values was 0.41, -0.18, 0.36, and -0.62 for w_1, w_2, w_3, and β, respectively.

4.3 Estimated Parameters and Fit of the Models

The parameter estimates and overall fit for each model are illustrated in Table 1. The models are ordered from least to most complex (in terms of the number of free parameters). Models (1), (2), and (3) were compared to model (0) in terms of BIC (i.e., the lowest BIC indicates the best-fitting model). For each dependent measure, model (1), (2) and (3) fit better than model (0). This indicates, that each additional free parameter increased the fit of the model being developed. Qualitative trends in the parameter estimates (across dependent measures) are clear in some respects and less clear in others. For example, the SBSODS did appear to contribute to the overall performance of model (3). In contrast, the parameter estimates for β indicate that advance visibility did not contribute to the fit of the largest model (3). However, advance visibility did appear to contribute to the fit of models (1) and (2). Possible reasons for these trends are

Table 1. The table depicts the estimated parameters of the models, the summed and squared error (SSE) as well as the Bayes' information criterion (BIC) transformation

dec dur: decision situation duration, head mov: number of head movements

map sw: number of map switches and map dur: map usage duration

	#Parameters	w_1	w_2	w_3	β	SSE	BIC	Model
dec dur	0	-	-	-	-	19.6649	-100.39	(0)
	1	-	-	-	1	7.2884	-170.5228	(2)
	2	0.151	-	-	0.737	4.4185	-203.7416	(1)
	4	0.5565	0.0326	0.4109	0	3.2591	-217.9328	(3)
head mov	0	-	-	-	-	25.7513	-80.1750	(0)
	1	-	-	-	1	8.7034	-157.2155	(2)
	2	0	-	-	0.788	2.1307	-258.4428	(1)
	4	0.9009	0.0991	0	0	1.0166	-305.3069	(3)
map sw	0	-	-	-	-	19.8388	-99.7385	(0)
	1	-	-	-	1	5.7005	-188.9526	(2)
	2	0.082	-	-	0.752	1.4792	-285.8140	(1)
	4	0.4386	0.0795	0.4819	0	0.8382	-319.7790	(3)
map dur	0	-	-	-	-	15.0279	-120.5680	(0)
	1	-	-	-	1	4.5029	-206.6400	(2)
	2	0.152	-	-	0.644	2.3217	-252.0042	(1)
	4	0.3249	0.2453	0.4298	0.038	1.997	-254.6682	(3)

briefly explored in section 5. We estimated parameters that would fit the models based on the time that was spent in a wayfinding decision situation, which is a commonly used measure for wayfinding complexity. Moreover, we estimated parameters in order to find a fit for the models based on the number of head movements, the number of gaze switches from the environment to the map as well as the total time spent on the map. These are measures that can serve as an indication for cognitive load. The results demonstrate that, for all measures, each additional parameter increased the overall fit of the operational model.

5 Discussion and Outlook

According to the evaluation results of the three linear operational models, a combination of environmental, instruction, and user factors is better suited for describing the complexity of a wayfinding decision situation than any single element or any combination of two of them. Advance visibility did not contribute to the fit of the largest model (3), which probably can be explained by the small differences in the obtained values.

The conceptual model of a wayfinding decision situation (as discussed in section 2.1) is more general than the operational model used for the evaluation. A number of factors possibly impacting the complexity of a decision situation have not been considered in our evaluation, such as signage at the decision points, the user's cultural background, or different types of instructions. As future work, studies investigating the influence of these factors on the complexity of a decision situation are required. The resulting enriched models will hopefully lead to significant and strong correlations with the study data.

Also, an analysis of the interrelation of these factors in a combined model will help to complement previous findings from the wayfinding literature about each single factor.

Another logical next step is the implementation of a pedestrian wayfinding assistant which recommends the route with the least complexity, based on the wayfinding decision situation model. One challenge in this context consists of defining a user model. Some properties of the user, such as spatial abilities, may not be available when a user starts the wayfinding assistant for the first time. One possible solution for this could be to learn parts of the user model during wayfinding (e.g., from wayfinding behavior or from interaction with the system).

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References

1. Allen, G.: Spatial abilities, cognitive maps, and wayfinding: Bases for individual differences in spatial cognition and behavior. In: Golledge, R.G. (ed.) Wayfinding Behavior - Cognitive Mapping and Other Spatial Processes, pp. 46–80. Johns Hopkins University Press, Baltimore (1999)
2. Bunch, R.L., Lloyd, R.E.: The cognitive load of geographic information. The Professional Geographer 58(2), 209–220 (2006)
3. Clark, A.: Being There: Putting Brain, Body, and World Together Again. MIT Press, Cambridge (1997)
4. Denis, M.: The Description of Routes: A Cognitive Approach to the Production of Spatial Discourse. Cahiers Psychologie Cognitive 16(4), 409–458 (1997)
5. Dogu, U., Erkip, F.: Spatial factors affecting wayfinding and orientation: A case study in a shopping mall. Environment and Behavior 32(6), 731–755 (2000)
6. Frank, A.U.: Different types of "times" in GIS. In: Egenhofer, M.J., Golledge, R.G. (eds.) Spatial and Temporal Reasoning in GIS, pp. 40–62. Oxford University Press, Oxford (1998)
7. Gärling, T., Lindberg, E., Mantyla, T.: Orientation in buildings: Effects of familiarity, visual access and orientation aids. Journal of Applied Psychology 68(1), 177–186 (1983)
8. Goldberg, D.E., Deb, K.: A comparative analysis of selection schemes used in genetic algorithms. Foundations of Genetic Algorithms, pp. 69–93 (1991)
9. Golledge, R.G.: Spatial behavior: A geographic perspective. Guilford Press (1997)
10. Golledge, R.G.: Wayfinding Behavior: Cognitive Mapping and Other Spatial Processes. Wayfinding Behavior. Johns Hopkins University Press (1999)
11. Haque, S., Kulik, L., Klippel, A.: Algorithms for reliable navigation and wayfinding. In: Barkowsky, T., Knauff, M., Ligozat, G., Montello, D.R. (eds.) Spatial Cognition 2007. LNCS (LNAI), vol. 4387, pp. 308–326. Springer, Heidelberg (2007)
12. Hegarty, M., Richardson, A.E., Montello, D.R., Lovelace, K., Subbiah, I.: Development of a self-report measure of environmental spatial ability. Intelligence 30(5), 425–447 (2002)
13. Holmqvist, K., Nyström, M., Andersson, R., Dewhurst, R., Jarodzka, H., Van de Weijer, J.: Eye tracking: A comprehensive guide to methods and measures. Oxford University Press (2011)

14. Hölscher, C., Meilinger, T., Vrachliotis, G., Brösamle, M., Knauff, M.: Up the down staircase: Wayfinding strategies in multi-level buildings. Journal of Environmental Psychology 26(4), 284–299 (2006)
15. Kiefer, P., Giannopoulos, I., Raubal, M.: Where am I? Investigating map matching during self-localization with mobile eye tracking in an urban environment. Transactions in GIS (2013)
16. Klippel, A.: Wayfinding choremes. In: Kuhn, W., Worboys, M.F., Timpf, S. (eds.) COSIT 2003. LNCS, vol. 2825, pp. 301–315. Springer, Heidelberg (2003)
17. Kuipers, B.J., Levitt, T.S.: Navigation and mapping in large scale space. AI Magazine 9(2), 25 (1988)
18. Lewandowsky, S., Farrell, S.: Computational modeling in cognition: Principles and practice. Sage Publications (2010)
19. Li, C., Longley, P.: A test environment for location-based services applications. Transactions in GIS 10(1), 43–61 (2006)
20. Lovelace, K.L., Hegarty, M., Montello, D.R.: Elements of good route directions in familiar and unfamiliar environments. In: Freksa, C., Mark, D.M. (eds.) COSIT 1999. LNCS, vol. 1661, pp. 65–82. Springer, Heidelberg (1999)
21. Mark, D.M.: Automated route selection for navigation. IEEE Aerospace and Electronic Systems Magazine 1(9), 2–5 (1986)
22. Montello, D.R.: Scale and multiple psychologies of space. In: Campari, I., Frank, A.U. (eds.) COSIT 1993. LNCS, vol. 716, pp. 312–321. Springer, Heidelberg (1993)
23. Montello, D.R.: Navigation. In: Shah, P., Miyake, A. (eds.) The Cambridge Handbook of Visuospatial Thinking, pp. 257–294. Cambridge University Press (2005)
24. O'Neill, M.J.: Evaluation of a conceptual model of architectural legibility. Environment and Behavior 23(3), 259–284 (1991)
25. Raubal, M., Panov, I.: A formal model for mobile map adaptation. In: Location Based Services and TeleCartography II, pp. 11–34. Springer (2009)
26. Raubal, M., Winter, S.: Enriching wayfinding instructions with local landmarks. In: Egenhofer, M., Mark, D.M. (eds.) GIScience 2002. LNCS, vol. 2478, pp. 243–259. Springer, Heidelberg (2002)
27. Reichenbacher, T.: Adaptation in mobile and ubiquitous cartography. In: Multimedia Cartography, pp. 383–397. Springer (2007)
28. Schneider, L.F., Taylor, H.A.: How do you get there from here? Mental representations of route descriptions. Applied Cognitive Psychology 13(5), 415–441 (1999)
29. Simon, H.A.: A behavioral model of rational choice. The Quarterly Journal of Economics, 99–118 (1955)
30. Weiser, P., Frank, A.U.: Cognitive transactions–a communication model. In: Tenbrink, T., Stell, J., Galton, A., Wood, Z. (eds.) COSIT 2013. LNCS, vol. 8116, pp. 129–148. Springer, Heidelberg (2013)
31. Weisman, J.: Evaluating architectural legibility way-finding in the built environment. Environment and Behavior 13(2), 189–204 (1981)
32. Werner, S., Long, P.: Cognition meets Le Corbusier - cognitive principles of architectural design. In: Freksa, C., Brauer, W., Habel, C., Wender, K.F. (eds.) Spatial Cognition III. LNCS (LNAI), vol. 2685, pp. 112–126. Springer, Heidelberg (2003)
33. Winter, S.: Route adaptive selection of salient features. In: Kuhn, W., Worboys, M.F., Timpf, S. (eds.) COSIT 2003. LNCS, vol. 2825, pp. 349–361. Springer, Heidelberg (2003)
34. Wolbers, T., Hegarty, M.: What determines our navigational abilities? Trends in cognitive sciences 14(3), 138–146 (2010)