Uncertainty in Wayfinding: A Conceptual Framework and Agent-Based Model*

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Abstract

Though the wayfinding process is inherently uncertain, most models of wayfinding do not offer sufficient possibilities for modeling uncertainty. Such modeling approaches, however, are required to engineer assistance systems that recognize, predict, and react to a wayfinder's uncertainty. This paper introduces a conceptual framework for modeling uncertainty in wayfinding. It is supposed that uncertainty when following route instructions in wayfinding is caused by non-deterministic spatial reference system transformations. The uncertainty experienced by a wayfinder varies over time and depends on how well wayfinding instructions fit with the environment. The conceptual framework includes individual differences regarding wayfinding skills and regarding uncertainty tolerance. It is implemented as an agent-based model, based on the belief-desire-intention (BDI) framework. The feasibility of the approach is demonstrated with agent-based simulations.

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1 Motivation

Wayfinding – the 'goal-directed and planned movement of one's body around an environment in an efficient way' [20] – can be modeled as a sequence of wayfinding decision situations [6] in which the wayfinder chooses from a set of possible paths. These decisions are made under uncertainty, where the degree of uncertainty depends on the situation: for instance, uncertainty will be higher while performing uninformed search [34] in a foreign city than while finding the way to one's regular workplace.

Navigation aids may help alleviate uncertainty in wayfinding. Different types of navigation aids, and different approaches for the generation and communication of wayfinding instructions through digital wayfinding assistants, have been considered over the years, including turn-by-turn instructions [13], you-are-here maps [12], digital 2D and 3D maps [14], adaptive signage [15], or haptic interfaces [28]. A particularly well-studied topic is the automated creation of route instructions based on landmarks [25]. For instance, choosing landmarks based on their saliency [24] aids at reducing uncertainty by helping the wayfinder match the instruction to the environment.

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While these approaches may alleviate uncertainty to some degree, a significant amount of uncertainty often remains: the user might be lacking the (spatial) abilities for interpreting the information [1], there may have been problems in the communication process [32], incongruent information that does not match the environment [29], or context factors the navigation assistant did not adapt to [23]. It is unlikely that it will be ever possible to completely erase uncertainty in wayfinding, which underlines the importance of taking the user's uncertainty into account for the design of wayfinding assistants.

A holistic understanding of uncertainty in wayfinding implies also an understanding of wayfinders' reactions to uncertainty. Brunyé et al., for instance, have found empirical evidence that the type of information source (human vs. GPS device) influences the decision made in situations of uncertainty [2]. Tomko and Richter have suggested that, under conditions of uncertainty, a wayfinder will eventually enter a particular wayfinding mode (*defensive wayfinding*) in which she is aware of a mismatch between instruction, expectations and environment, thus proceeding cautiously and investing excessive mental effort for correcting the mismatch [29]. This perspective on uncertainty in wayfinding is particularly interesting because it transcends the notion of situative uncertainty (*which factors influence uncertainty at decision point p?*) to a more process-oriented view on uncertainty (*how does uncertainty influence the wayfinder's cognitive processes over time?*). The 'defensive wayfinding' model [29], however, remains conceptual and largely informal.

Overall, we note that, while wayfinding literature has touched upon and discussed uncertainty from different perspectives, a computational model of uncertainty in wayfinding which would allow wayfinding assistants to have an explicit notion of and take their user's uncertainty into account is still missing.

Here, we take important steps towards such model: we introduce a conceptual framework which allows to model uncertainty in wayfinding as a result of non-deterministic reference system transformations (building on ideas from [11]). The conceptual framework enables to include all three aspects of a wayfinding situation into a model: the wayfinder, the instruction, and the environment. The presented framework covers both, a situational and a process-oriented view on uncertainty in wayfinding, and allows to capture individual differences (since people have different dispositions regarding their ability to deal with uncertainty [5]).

Based on this general framework, we further develop an agent-based model (ABM) of landmark-based wayfinding under uncertainty in an unfamiliar environment. In the past, numerous studies have aimed at developing artificial agents with navigation capabilities, including more general cognitively inspired computational frameworks, such as TOUR [17], but also practical applications from the ABM community (e.g. [22, 9]). More closely related to our work are studies on software agents which comprehend and follow route instructions, e.g., [18, 30], who present agents capable of following natural language route instructions, [33], whose probabilistic agent interprets ambiguous direction-based route instructions in real-world path networks, or [7], who use an agent for evaluating the reliability of a complexity-reducing route computation algorithm.

To the best of our knowledge, however, there has so far been no ABM which is based on a comprehensive concept of how uncertainty is created from the interplay of agent, environment and instruction, or its subsequent effects on the behavior of the wayfinder agent. These insights, however, are needed for developing and testing uncertainty-aware assistance systems. In this paper, thus, we demonstrate on an exemplary implementation of our model its capabilities for simulating wayfinding situations of differing complexity.

The paper is structured as follows: Section 2 explains prior work on reference system transformations in wayfinding [11]. Section 3 introduces our conceptual framework of uncertainty in wayfinding which provides the basis for the development of an ABM of wayfinding under uncertainty (see Section 4). An exemplary implementation of the ABM and simulation results are presented in Section 5, before Section 6 concludes this paper.

2 Modeling Wayfinding With Reference System Transformations

This section shortly reflects on the role of spatial reference system transformations in wayfinding (refer to [11, section 2.1] for details). Spatial reference systems are a core concept of spatial information theory as they are used to encode (externally or internally), reason about, and communicate about locations by both, humans and machines [4, 16, 27]. Three types of reference systems are relevant for wayfinding: *egocentric* (self-to-object), *allocentric* (object-to-object), and *survey reference systems* (relative to the earth's surface or other ground phenomena).

Egocentric reference systems are aligned with the body and used by the wayfinder to refer to locations in vista space [19], such as *'left of that restaurant over there'*. Such egocentric locations are the output of a wayfinding decision and serve as input for locomotion. Allocentric reference systems enable the reference to locations across individuals and independent from the current point of view. They can therefore be used for representing instructions, such as '*(take the road) in front of the restaurant'*. A reference system transformation (from allocentric to egocentric) is necessary in order to match these instructions with the current field of view. Survey reference systems, such as cartographic maps or mental spatial representations ('cognitive maps' [31]), represent locations with their relation to other locations and are therefore used for route planning. The authors of [11] modeled the output of the route planning process as a sequence of (allocentric) instructions. Route planning therefore requires a transformation from survey to allocentric locations (e.g., *'North of the restaurant symbol'* → *'in front of the restaurant'*).

The model in [11] was intentionally left underspecified in several aspects. For instance, it did not describe how the wayfinder behaves if a reference system transformation is not deterministic, which happens often in realistic use cases. This paper focusses on the uncertainty caused by non-deterministic reference system transformations, thus building on the core ideas discussed in [11].

3 Conceptual Framework

Here, uncertainty is considered as a wayfinder's lack of knowledge about relevant aspects of the wayfinding situation, which is defined by the interplay of the environment (Sections 3.1 and 3.2), the wayfinder (Section 3.3), and the instruction (Section 3.4) [6]. In this section, we focus on route following and develop a conceptual framework for modeling uncertainty along these three dimensions.

3.1 Uncertainty and Spatial Reference Systems in Wayfinding

For a wayfinder standing at a decision point, the most fundamental form of uncertainty relates to the question which path to take next (*path choice uncertainty*). Here, we argue that path choice uncertainty is caused by other types of uncertainty which originate from the cognitive sub-processes involved in wayfinding. For instance, the wayfinder may be uncertain about whether she is still on the correct route, whether the object she perceives in front of her matches the landmark refered to in a route instruction, or where she would locate her current position on a map. Following the idea of [11] (see also Section 2) of reference system transformations as a core concept for a model of wayfinding, we here suggest that

► **Supposition 1.** *Uncertainty in wayfinding is always related to a spatial reference system.*

Thus, uncertainty can be present for each of the three types of spatial reference systems relevant for wayfinding:

- *Egocentric uncertainty*: where in my egocentric view is location L_e? An important egocentric uncertainty is path choice uncertainty: where in my egocentric view is the path I should take?
- *Allocentric uncertainty*: where is L_{a1} located, relatively to L_{a2}? In path following [34], an important allocentric uncertainty is the *on-route uncertainty*: is my current location on the route I was planning to follow?
- *Survey uncertainty*: where is L_s in a given survey reference system, e.g., where is the wayfinder's location on a map?

Note that in our concept uncertainty in different spatial reference systems may have different degrees at the same time. For instance, a wayfinder could be very certain about her position on a map, but at the same time very uncertain about which path to take (and vice versa).

3.2 Non-Deterministic Reference System Transformations in Wayfinding

A wayfinder needs to transform information between reference systems in order to successfully solve the wayfinding problem (see Section 2 and [11]). The transformation processes are non-deterministic, which causes uncertainty:

► **Supposition 2.** *Uncertainty in wayfinding can be modelled as being caused by non-deterministic spatial reference system transformations.*

For instance, suppose that in an instruction-based wayfinding situation, the allocentric instruction *'(take the road) in front of the restaurant'* can be transformed to three egocentric locations – the entries to three alternative roads – as follows: ($L_{E,1}$, 0.1), ($L_{E,2}$, 0.2), ($L_{E,3}$, 0.15). Numbers describe how well these locations fit to the instruction (*fit distribution*). In this example, all three location options have rather low fit values[1], meaning that the allocentric location cannot be mapped well (e.g., none of the egocentric objects can be clearly recognized as a restaurant).

We assume that this kind of situation will increase the wayfinder's allocentric uncertainty: *'is the instruction really meant for my current location? Did I go wrong in one of my previous decisions?'*[2]. On the other hand, a high maximum fit will re-assure the wayfinder about being on route, even though she might have felt uncertain before (= decrease allocentric uncertainty). Similarly, while transforming from allocentric to a survey system, a low maximum fit may indicate that the survey system does not contain a correspondent for the allocentric location (e.g., the map shows a different area), which would increase uncertainty. These examples lead us to:

[1] Without loss of generality, we here assume a scale [0..1] for *fit*. Note that a fit distribution is not a probability distribution, i.e., fits in a particular decision situation do not sum up to 1.

[2] [29] would characterize situations with low maximum fit as having a high *detectability* of mismatch between instruction and environment.

▶ **Supposition 3.** *A non-deterministic spatial reference system transformation will increase uncertainty if the maximum fit value is low, and decrease uncertainty if the maximum fit value is high.*

Ambiguity has been identified as an important factor determining the success of wayfinding [29]. With the fit distribution introduced above, we can easily define:

▶ **Supposition 4.** *A non-deterministic spatial reference system transformation will increase uncertainty if the ambiguity of the fit distribution is high.*

Ambiguity occurs if the maximum fit value is close to the fit values of other options[3]. For instance, the instruction *'in front of the restaurant'* could have an equal fit to two options if there is more than one restaurant. Note that, in our model, ambiguity does not require the maximum fit to be particularly high. The fit distribution given in the example above (0.1, 0.2, 0.15) would be ambiguous, because this kind of distribution makes it hard for the wayfinder to decide between the three options.

3.3 Coping Strategies, Individual Differences

With the suppositions proposed so far, we have modeled *uncertainty changes over time*, which includes both, increase and decrease of uncertainty. As a next step, we look at wayfinders' (individual) reactions to uncertainty. Similar to the concept of defensive wayfinding introduced in [29], we include a wayfinder's reactions to uncertainty as follows:

▶ **Supposition 5.** *If uncertainty in a spatial reference system reaches an uncertainty threshold, the wayfinder applies one or several* coping strategies *in order to reduce uncertainty in that particular reference system. The threshold is determined by the wayfinder's characteristic* uncertainty tolerance*.*

Uncertainty tolerance describes the wayfinder's tendency to continue non-defensive wayfinding (i.e., without coping strategy) in situations of uncertainty. It is motivated by psychological research which has found that humans have a disposition with regards to their behavior in uncertain situations [5]. Here, we assume that uncertainty tolerance is influenced by at least three factors: 1) an individual disposition, 2) the wayfinder's self-estimation of her wayfinding skills (see below), 3) the impacts of getting lost for the given task context (e.g., arriving late for a dinner appointment vs. missing a plane).

Coping strategies may reduce uncertainty but require time. A wayfinder who performs coping strategies frequently will have fewer uncertain situations, leading to fewer errors, higher likelihood of reaching the destination (high effectiveness), but need more time (low efficiency). Examples for coping strategies include increasing visual monitoring of the environment, asking an instructor to point to the direction one needs to take, asking a local person to help with disambiguation of landmarks, or performing self-localization on a you-are-here map.

A second individual difference, besides uncertainty tolerance, is certainly determined by the agent's *wayfinding skills* (e.g., [8])

▶ **Supposition 6.** *The lower the wayfinding skills are, the more will the fit distribution estimated by a wayfinder during a spatial reference system transformation deviate from a ground-truth fit distribution.*

[3] We introduce one possible formula for ambiguity in Section 4.

While uncertainty tolerance is defined w.r.t. one particular reference system, the wayfinding skill is related to a type of reference system transformation. For instance, some wayfinder may have high wayfinding skills for matching landmark-based instructions to the environment (allocentric to egocentric), but low map reading skills (survey to allocentric).

3.4 Generating Uncertainty-Aware Route Instructions

The algorithms listed in Table 1 specify three possible strategies for selecting an instruction which describes the destination edge e_{dest} when arriving from edge e_{orig} at a decision point *dp*. The algorithms are executed for each decision point along a previously created route, such as the shortest or the simplest alternative [3].

Algorithm 1 generates a finite set of possible instructions and returns the one with the highest fit. Since Algorithm 1 does not take ambiguity into account, there could exist a different edge for which the same instruction has an even better fit. For instance, the approach proposed by [24] generates landmark-based instructions based on the saliency of landmark candidates (from visual, semantic, and structural attraction), but does not consider whether there are other landmark candidates of the same type at the decision point.

Algorithm 2 resolves this by comparing the fit of instruction and target edge to the fit of that instruction to all other edges. If there is a non-target edge for which the instruction fits better, the instruction is discarded and one with lower fit is tested the same way. It may happen that no instruction can be generated if all potential instructions for the target edge have a better fit to some other edge. In that case, the calling route generation algorithm would need to find a route through a different decision point.

Similarly, **Algorithm 3** first generates all instructions for the target edge and then discards all those which have a better fit somewhere else. For each of the remaining instructions the ambiguity of the instruction is computed and combined with target edge fit. The one which maximizes the combined score is returned. The rationale behind Algorithm 3 is that a wayfinder with low wayfinding skills might perceive a fit distribution which deviates from the distribution assumed by the algorithm (see Supposition 6).

4 An Agent-Based Model of Wayfinding Under Uncertainty

In this section, we describe an agent-based model of wayfinding under uncertainty. The suppositions introduced in the conceptual framework (Section 3) are here operationalized for the particular case of wayfinding with landmark-based instructions in an unknown environment (i.e., we exclude the level of survey knowledge here). It is further assumed that the level of uncertainty changes only at decision points (see discussion in Section 6).

4.1 The Environment

The environment is modeled as a directed weighted graph with decision points (DP) as nodes, and paths as edges (E). Each decision point features a (finite) set of objects (O_{dp}), which serve as potential landmarks in wayfinding instructions. A spatial configuration attribute ($config_{dp}$) describes for each *dp* the allocentric spatial relations between its adjacent path edges and inherent objects, based on a *fit distribution* over the available tuples of edge, object, and relation ($config_{dp} \subseteq E \times O_{dp} \times Rel \times [0..1]$). For instance, $(e_3, o_7, rel_x, 0.9) \in config_{dp10}$ would specify that, at decision point *dp10*, the edge e_3 can be described as being located in relation rel_x to object o_7 with a *relfit* of 0.9. Note that we remain on a high level of

Table 1 Three instruction generation algorithms for wayfinding under uncertainty (pseudo code). The algorithms assume: (a) a function which generates a finite list of possible instructions for describing a destination edge at a decision point, (b) a *fit*() function which computes how well an instruction fits to an edge, (c) a function *amb*() which computes the ambiguity of an instruction at a decision point, (d) a *combinedscore*() function which averages fit and ambiguity.

Algorithm 1 (local fit optimization)
in: DecisionPoint dp, Edge e_{orig}, Edge e_{dest}, **out**: Instruction

```
I ← Generate possible instructions for e_dest.
fit(i, e_dest) ← Calculate for each instruction i ∈ I the fit to e_dest.
Return i ∈ I, which maximizes fit(i, e_dest).
```

Algorithm 2 (max fit optimization)
in: DecisionPoint dp, Edge e_{orig}, Edge e_{dest}, **out**: Instruction

```
I ← Generate possible instructions for e_dest.
fit(i, e_dest) ← Calculate for each instruction i ∈ I the fit to e_dest.
I′ ← Sort I by fit(i, e_dest) in descending order.
for each i′ ∈ I′
    fit(i′, e′) ← Calculate the fit for i′ to each e′ ∈ dp.getEdges() \ {e_orig, e_dest}
    if not exists e′ with fit(i′, e′) > fit(i′, e_dest)
        return i′
return Could_not_create_instruction.
```

Algorithm 3 (combined fit and ambiguity optimization)
in: DecisionPoint dp, Edge e_{orig}, Edge e_{dest}, **out**: Instruction

```
I ← Generate possible instructions for e_dest.
fit(i, e_dest) ← Calculate for each instruction i ∈ I the fit to e_dest.
for each i ∈ I
    fit(i, e) ← Calculate the fit for i to each e ∈ dp.getEdges() \ {e_orig, e_dest}
    if exists e with fit(i, e) > fit(i, e_dest)
        I.remove(i)
amb(i, dp) ← Calculate for each instruction i ∈ I the ambiguity at dp.
Return i ∈ I, which maximizes combinedscore(fit(i, e_dest), amb(i, dp)).
```

abstraction here: we neither model the location of objects in coordinate space, nor explicit relations, such as ‘in front of’.

Here, in a wayfinding instruction, the corresponding object instance is referred to by an object type (from a finite set T), such as ‘a restaurant’ or ‘a blue house’. Object instances can have more than one type. Function $typefit_{dp} : (O_{dp} \times T) \rightarrow [0..1]$ describes how well an object fits to a certain type. The *fit distribution* over location candidates of the conceptual framework (refer to Section 3.2), therefore, results from a combination of the according *typefit* and *relfit* values.

4.2 The Agent

The cognitive architecture of our wayfinder agent is based on the widely-used belief-desire-intention (BDI) framework [21]. The agent’s behavior is primarily motivated by a desire (reaching the destination node), its knowledge base is represented as separate beliefs, and its intentions refer to and can trigger particular behavior. As explained in Section 3.3, agents

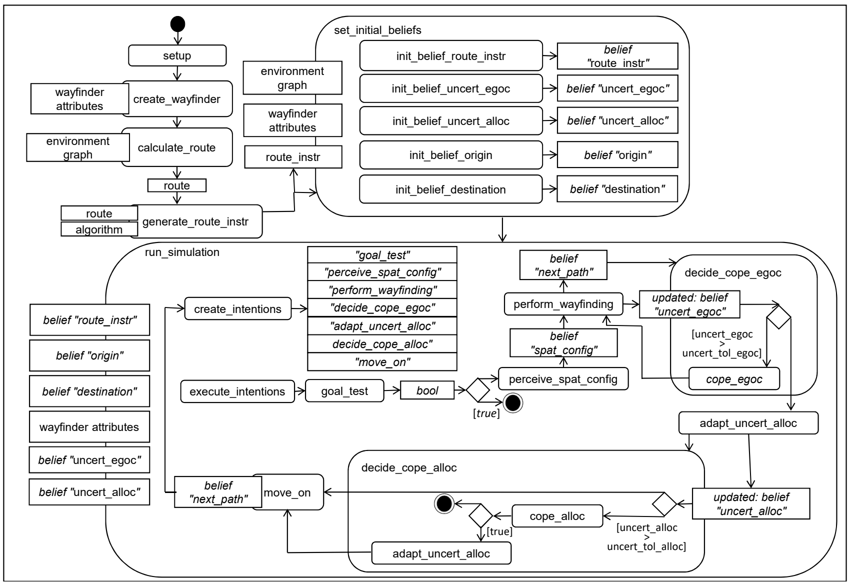

Figure 1 Overview: an agent-based model of wayfinding under uncertainty.

have individual differences w.r.t. wayfinding skills (Supposition 6) and uncertainty tolerance (Supposition 5). Wayfinding skills are here further distinguished between the skill to accurately assess the spatial relations (*relfit* values) between pairs of object and edge (*wayf_rel_skill*), and the skill to recognize the type (*typefit* values) of an object (*wayf_type_skill*).

Regarding uncertainty tolerance, we distinguish between uncertainty tolerance on egocentric and on allocentric level. The first, *uncert_tol_egoc*, reflects the tolerance regarding path choice uncertainty. A wayfinder with low *uncert_tol_egoc*, for instance, will have a high desire to make sure she makes the correct decision, which means she will often apply an egocentric coping strategy (e.g., ask somebody whether that building over there is of type t). The latter, *uncert_tol_alloc*, reflects the tolerance regarding on-route uncertainty. For instance, a wayfinder with low *uncert_tol_alloc* has a high desire to always know whether she is still on the route.

4.3 The Wayfinding Process

4.3.1 Initialization, goal test and perception

Figure 1 illustrates our model of the wayfinding process. After an environment graph has been built up in a setup procedure, a wayfinder agent is created and positioned at the start node of the route. Then, the shortest route from the start to the destination node is calculated, and, using one of the algorithms described in Section 3.4, translated into a route description, i.e., an ordered sequence $route\_instr = [i_1, i_2, ..., i_j]$ where each instruction i consists of one relation and one object type, $i_k \in Rel \times T$. While the actual route is unknown to the wayfinder agent, the *route_instr*, among other initial settings, is stored in its belief structure (*set_initial_beliefs*).

After setup and initialization, the wayfinding process starts with the creation of a stack of intentions (*create_intentions*). The wayfinder agent processes the stack incrementally, triggering the corresponding behavioral procedures (*execute_intentions*). It begins by checking whether the destination node has been reached (*goaltest*). If so, the wayfinding has been successful and the simulation stops; if not, the agent perceives the $config_{dp}$ of the dp it is currently located at and stores it in its belief structure. In order to account for different wayfinding skills (see Supposition 6), the true $config_{dp}$ is not directly perceived, but distorted by randomly altering *relfit* and *typefit* values. The probability distribution for the magnitude of this error is determined by the agent's *wayf_rel_skill* and *wayf_type_skill* attributes (by setting the standard deviation of a normal error distribution with a mean of 0).

4.3.2 Instruction matching, ambiguity and uncertainty

In the next procedure (*perform_wayfinding*), the agent interprets the route instruction w.r.t. the perceived $config_{dp}$: given instruction $i = (rel, t)$ at decision point dp, it identifies the adjacent edge e_{max} for which i fits best and stores it as a *next_path* belief.

As described in Suppositions 2 and 4, however, the agent can be more or less uncertain about the correctness of this decision, depending on the closeness of the fit values of the alternative edges (ambiguity). We here use the following formula for quantifying ambiguity:

$$ambiguity_{dp} = maxfit_{dp} - \frac{\sum_{i=1}^{n} typefit_i * relfit_i}{n}$$

where $maxfit_{dp} = max(typefit * relfit)_{dp}$ and ambiguity is hence calculated as the difference between the maximum possible product of *typefit* and *relfit* at *dp* and the mean of the product of the same (rel, t) for all alternative edges.

The resulting ambiguity value is taken as perceived egocentric uncertainty of choosing a path at this *dp*, and is stored as an *uncert_egoc* belief. In a following *decide_cope_egoc* procedure, the agent tests whether *uncert_egoc* exceeds the *uncert_tol_egoc* attribute, as described in Suppositions 5 and 6, and would therefore require a coping strategy. In this case, a *cope_egoc* procedure is triggered, which reduces uncertainty by providing the agent with the true $config_{dp}$ with undistorted fit values. Please note that other forms of *cope_egoc* strategies would also be thinkable here.

Based on the updated fit values, the agent then repeats *perform_wayfinding*, and adapts the uncertainty on the allocentric level (*adapt_uncert_alloc*). This step consists of two sub-processes: first, the influence of the $maxfit_{dp}$ value is assessed. The following formula is based on the assumption that $uncert\_alloc'$ is set to 0.0 for $maxfit_{dp} = 1.0$, set to 1.0 for $maxfit_{dp} = 0.0$, and does not change for $maxfit_{dp} = 0.5$ (with linear interpolation between):

$$uncert\_alloc' = \begin{cases} maxfit_{dp} \leq 0.5 : & (2 * uncert\_alloc - 2) * maxfit_{dp} + 1\,, \\ maxfit_{dp} > 0.5 : & -2 * uncert\_alloc * maxfit_{dp} + 2 * uncert\_alloc\,. \end{cases}$$

As a second sub-process, the potential increase in uncertainty is taken into account which results from a product of the agent's estimation of how likely she is located at the correct decision point $(1 - uncert\_alloc')$ and the likelihood of making a correct decision with regards to which path to follow from the *dp*.

$$uncert\_alloc'' = 1 - ((1 - uncert\_alloc') * (\frac{maxfit_{dp}}{\sum_{i=1}^{n} typefit_i * relfit_i}))\,.$$

The belief *uncert_alloc* is updated with the new value *uncert_alloc*" and then compared to the agent's individual *uncert_tol_alloc* attribute to check whether a *cope_alloc* strategy must be triggered (see Supposition 5). This procedure simply provides feedback to the agent whether its location is still on the intended route or not. If *cope_alloc* returns false, the simulation stops and the agent is lost. If *cope_alloc* returns true, *uncert_alloc* is set to 0. Finally, the agent moves along the *next_path* identified previously to the next *dp*.

5 Simulation Experiment

In this section, we describe results of a simulation with an implementation of our ABM in the agent-based simulation environment NetLogo (`http://ccl.northwestern.edu/netlogo/`). The simulation mainly serves as a validation of the feasibility of the modeling approach. We are particularly interested in answering two questions: (1) is our model capable of simulating wayfinding situations of differing complexity?, and (2) can we model individual differences among wayfinder agents?

5.1 Implementation and Parameter Settings

In the implementation we modelled wayfinders, decision points, and environmental objects as separate classes of agents, and connected the decision points with undirected links to receive a path network. For our BDI-structure, we borrowed from an implementation done by [26]. Random graph networks with 70-80 decision points were created. In order to maintain realistic structural network properties, we enforced small-world structures with average node degrees between 2-4.75, which roughly corresponds to the characteristics which [10] identified for real-world urban networks.

A total of 24.576 simulation runs were executed, resulting from the following systematic variation of parameters (256 agents $\times$ 3 instruction generation algorithms $\times$ 32 environments):

- **Agent**: different combinations of skill and uncertainty tolerance levels: *wayf_rel_skill*, *wayf_type_skill*, *uncert_tol_egoc*, *uncert_tol_alloc*, each $\in \{0.00, 0.33, 0.66, 1.00\}$
- **Environment**: 2 random environments for each of 16 different complexities by varying: *mean_main_rel_distr* and *mean_main_type_distr* (each $\in \{0.5, 0.75\}$), *mean_minor_rel_distr* and *mean_minor_type_distr* (each $\in \{0.25, 0.5\}$). These parameters determined the mean of normal distributions for the generation of *typefit* and *relfit* distributions. We assumed the existence of 10 abstract types of objects, and assigned up to two of them as main types to object instances, which would likely receive higher *typefit* values than the other, minor types. The same was done for the *relfit* values of combinations of edge and object. Thus, lower mean values for main, and higher mean values for minor *typefit* and *relfit* have a higher probability to increase ambiguity and decrease $maxfit_{dp}$ at decision points.
- **Instruction generation algorithm**: Algorithm 1, 2, 3 (see Section 3.4, Table 1).

5.2 Simulation Test

We analyse the results in terms of effectiveness (Has the agent successfully reached the destination?) and efficiency (How often have those agents which reached the destination performed a coping strategy?).

For the analysis of *effectiveness*, we aggregate results regarding the *challenge of the wayfinding situation*, which is determined by the agent's wayfinding skills and the ambiguity of the environment as follows:

- *High challenge*: within the upper half of the total average ambiguity distribution along the route, and the lower half of the total average $maxfit_{dp}$ distribution along the route, and low wayfinding skills (*wayf_rel_skill* and *wayf_type_skill* $<= 0.33$)
- *Low challenge*: within the lower half of the total average ambiguity distribution along the route, and the upper half of the total average $maxfit_{dp}$ distribution along the route, and high wayfinding skills (*wayf_rel_skill* and *wayf_type_skill* $>= 0.66$)

Table 2 Wayfinding success rates for combinations of: uncertainty tolerance (lines), challenge of the decision situation (columns) and instruction generation algorithm (A1, A2, A3, see Table 1).

	high challenge			low challenge		
	A1	A2	A3	A1	A2	A3
high uncertainty tolerance	0.055	**0.063**	0.046	0.142	0.186	**0.228**
low uncertainty tolerance	0.159	**0.497**	0.426	0.191	**0.519**	0.475

These were combined with high (*uncert_tol_egoc* and *uncert_tol_alloc* >= 0.66) or low (*uncert_tol_egoc* and *uncert_tol_alloc* <= 0.33) uncertainty tolerance values, yielding in the results listed in Table 2.

The table shows the normalized success rates (successful runs / total runs) and the best performing route instruction algorithm. It can be seen that the success rates differ to a great degree, high challenge generally leading to lower success rates, especially in the case of a high uncertainty tolerance (agent refrains from using coping strategies). With regards to the performance of the different route instruction algorithms, it can be seen that in most cases, the more elaborate algorithms clearly outperform simple Algorithm 1. The differences between Algorithm 2 and 3, however, are less clear. Especially in case of low uncertainty tolerance, the potentially higher $maxfit_{dp}$ provided by Algorithm 2 might represent the better choice, whereas the ambiguity-reducing strategy of Algorithm 3 can provide an advantage for agents with a high uncertainty tolerance in relatively low challenging environments.

With regards to *efficiency*, we observe a clear effect of wayfinding skills on the normalized number of *cope_egoc* strategies (low skills: 0.465 vs. high skills: 0.306). Moreover, with growing *uncert_tol_egoc* and *uncert_tol_alloc*, not surprisingly, the number of coping strategies drop sharply (e.g. for *cope_egoc* strategies: low uncertainty tolerance: 0.681 vs. high uncertainty tolerance: 0.080).

Hence, as can be seen particularly from the differing results on effectiveness listed in Table 2, our ABM was indeed capable of simulating wayfinding situations of varying complexity. Individual differences between wayfinder agents are also observable and especially apparent in our results on efficiency.

6 Discussion and Conclusion

We have presented a conceptual framework of uncertainty in wayfinding and used it as a basis for an ABM. In an exemplary implementation, we demonstrated its capability to model uncertainty as a result of non-deterministic reference system transformations in different wayfinding situations consisting of agent, environment and instruction.

While uncertainty has certainly been addressed in wayfinding research before (e.g., [29]), our framework addresses the topic from a novel perspective and has features which make it attractive for future applications to uncertainty-aware wayfinding assistants. In particular, it covers the dynamic aspect of uncertainty (over several decision points) and allows to differentiate between uncertainty on different levels of spatial reference systems.

Although our model currently involves highly abstracted representations of the agent and the environment, it is illustrated how it can inform the choice of an algorithm for the generation of route instructions based on the individual characteristics of wayfinder and environment. Such understanding on the conceptual level can be of value for the design of future wayfinding assistant systems which take their users' uncertainty into account.

However, there are also some shortcomings. Some concepts and processes in the ABM are drastically simplified, including the particular graph representation of the environment with spatial configurations of highly abstracted object types and spatial relations. Still, however, we expect that our fundamental concepts can be applied to more realistic environmental models as well. A further point of simplification is the representation of the wayfinding skills as determinants of a random error distribution in fit perception. Moreover, due to our focus on wayfinding in unknown environments, we did not model transformations from and to survey reference systems, such as maps. The ABM assumes that uncertainty changes only at decision points. This is a simplification because (ambiguous) reference system transformations may also occur while moving between decision points when the observed environment does not match the wayfinder's expectations (route monitoring).

Still, however, our work is valuable as a conceptual basis for the development of uncertainty-aware wayfinding assistance systems. For future work, we aim to apply the simulation to real-world urban networks. Further, user experiments would be required to gain a deeper insight on how humans perceive and react to uncertainty in different wayfinding decision situations. Moreover, it would be interesting to investigate the influence of specific coping strategies on egocentric, allocentric, and survey uncertainty.

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