A Resource-Rational Account of Information Scent in Navigation

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Abstract

Users navigating hierarchical information spaces exhibit trial-and-error behavior, such as backtracking and revisits. Information Foraging Theory explains these patterns through information scent, an estimate of the value of pursuing a link based on semantic cues. However, existing formulations often treat scent as a static, local evaluation, failing to account for how these estimates are revised under cognitive constraints during sequential decision-making. We propose a resource-rational account that conceptualizes information scent as a memory-mediated representation of observations under limited cognitive resources. In this framework, "resources" refer to working memory capacity, the temporal decay (forgetting) of memory traces, and the cost of sequential inspection. We argue that trial-and-error navigation behavior is not irrational noise, but a resource-rational adaptation to limited memory and costly information acquisition. We formalize this account in a computational model of sequential decision-making under limited observability and cognitive constraints. Simulations reproduce established difficulty and hierarchy-depth effects. Furthermore, manipulating the effective planning horizon systematically alters structural metrics such as lostness, linking navigation organization to sequential control. Together, these findings provide a theoretical reinterpretation of information scent as resource-constrained sequential decision-making.

Keywords: Information Scent; Resource Rationality; Sequential Decision Making; POMDP; Belief-MDP; Hierarchical Navigation

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Introduction

Navigating hierarchical information spaces is cognitively demanding. Users rarely follow optimal paths and instead exhibit systematic trial-and-error behavior, including backtracking, revisits, and premature commitments to suboptimal links (Pirolli & Card, 1999; Fu & Pirolli, 2007).

Information Foraging Theory (Pirolli & Card, 1999) explains these behaviors through information scent, interpreted as a local estimate of link utility derived from semantic cues. Drawing on the Marginal Value Theorem (MVT) (Charnov, 1976), IFT characterizes navigation as a value-guided process in which users estimate the expected benefit of pursuing a link based on information scent. However, most implementations treat scent as a step-wise, static signal, without modeling how such estimates evolve across time under cognitive constraints (Kitajima, Blackmon, & Polson, 2000; Blackmon, Polson, Kitajima, & Lewis, 2002; Fu & Pirolli, 2007).

A complementary line of work in resource-rational modeling argues that human behavior reflects adaptation to cognitive constraints, including limited working memory and processing cost (Simon, 1956; Lieder & Griffiths, 2020). These approaches formalize how decision policies adjust under such constraints but have rarely been applied to the cue-driven structure central to information foraging. The relationship between scent-based value estimation and resource-constrained belief updating therefore remains theoretically underdeveloped.

We argue that this gap can be resolved by reconceptualizing information scent as an input to implicit belief updating rather than as a direct decision variable (Kitajima et al., 2000; Fu & Pirolli, 2007). The core motivation of this framework is that navigation is an active, sequential, and resource-limited decision problem. Users do not passively receive information scent as an immediately accessible action value; rather, scent cues provide partial and noisy observations about an unobserved target location. These observations are integrated under constraints on working memory capacity, temporal decay, and inspection effort. Under this formulation, trial-and-error behaviors—such as premature commitment, backtracking, and revisits—naturally emerge from the interaction between sequential decision-making and cognitive limitations, shifting control from local evaluation to long-horizon planning. We use the term resource-rational in this constrained sense: the model does not assume explicit, metacognitive management of cognitive resources by the user. Instead, it formalizes how rational action is shaped and constrained by limited memory (capacity K and decay λ), observation noise(σ^2), action costs, and bounded sequential foresight (γ). The POMDP framework provides the precise technical tool to formalize this cognitive theory, mapping task utility and bounded resource constraints directly onto the agent's mathematical policy.

This work makes three contributions:

(1) **Conceptual:** We reinterpret information scent as a memory-mediated representation of observations that supports implicit belief updating over hidden target locations, rather than as a cue directly driving action selection.

(2) **Computational:** We formalize hierarchical navigation as a POMDP in which noisy scent observations and memory limits jointly shape belief dynamics over time.

(3) **Explanatory:** We show that this resource-constrained belief framework reproduces established effects of task difficulty, hierarchy depth, and target position, and accounts for

them through belief dynamics under constraints.

Related Work

Computational Models of Navigation and Scent

Computational modeling of web navigation has operationalized information scent in several ways. Analytical models such as CoLiDeS (Kitajima et al., 2000) and CWW (Blackmon et al., 2002) compute semantic similarity between user goals and link labels to predict link choice and navigation cost. These models provide strong quantitative predictions but assume stable evaluation of link values at each step.

Cognitive architecture models, including SNIF-ACT (Fu & Pirolli, 2007), embed scent evaluation within ACT-R, introducing sequential inspection and satisficing thresholds. While ACT-R (Anderson & Lebiere, 1998) incorporates activation decay and memory dynamics, scent is not represented as a probabilistic belief state over hierarchical locations that evolves under explicit memory constraints within the decision state. As a result, navigation is modeled through rule-based control rather than belief-level sequential planning. In contrast, our approach treats trial-and-error trajectories through a resource-rational lens. Backtracking and detours are modeled not as erratic execution errors, but as adaptations of an agent managing long-horizon utility under noisy and decaying observations.

Resource-Constrained Sequential Decision Models

Resource-rational frameworks model behavior as optimal under cognitive constraints such as limited working memory and computational cost (Simon, 1956; Lieder & Griffiths, 2020). These approaches have been applied to perception and decision-making, often using sequential or partially observable formulations. However, these models do not treat information scent as a representation of observations that informs belief updating within the decision process.

Model

To formalize the resource-rational account proposed above, we model scent-based navigation as sequential decision making under cognitive constraints as Figure 1 shows. The architectural novelty of this model lies in its generative nature: rather than prescribing a set of heuristic rules to simulate user actions, navigation strategies are mathematically derived through policy optimization under bounded internal capacity. The following modeling principles detail how these core cognitive constraints are operationalized within the agent's internal environment, providing the theoretical foundation before its formal mathematical implementation as a Partially Observable Markov Decision Process (POMDP).

Modeling Principles

Resource Rationality Following resource-rational accounts of optimal behavior under cognitive constraints, we assume that navigation reflects utility maximization subject to internal limitations.

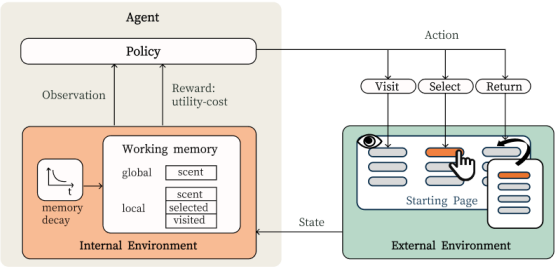


Figure 1: *Model architecture.* The model formalizes navigation in a hierarchical information space (e.g., a menu) as sequential decision making under uncertainty. At each step, the agent may inspect a link, select an option, or return to a previous page. Each option has a latent information scent that becomes partially observable through inspection and is corrupted by perceptual noise. Observed cues are stored in working memory, where capacity limits and temporal decay constrain their availability for future decisions.

In our model, these constraints are instantiated as: (a) perceptual uncertainty, modeled as stochastic scent observations with variance σ^2; (b) working memory constraints, including limited capacity K and temporal decay λ; and (c) a per-step action cost reflecting cognitive effort and the opportunity cost of continued exploration.

Under this formulation, behaviors such as premature commitment and backtracking arise as resource-rational adaptations to uncertainty and resource limitations.

Sequentiality Navigation unfolds as a sequential decision process under uncertainty. Users alternate between information-gathering actions (e.g., inspecting links to reveal scent) and commitment actions (e.g., selecting or returning). Each action changes both the agent's location in the hierarchy and the evidence available for future decisions. Therefore, the value of a current action depends on its anticipated downstream consequences.

We formalize this property through the Bellman action-value equation:

$$Q^{\pi}(s,a) \;=\; E[r_t + \gamma V^{\pi}(s_{t+1}) \,|\, s_t = s, a_t = a], \qquad (1)$$

where s denotes the current state (including hierarchical position and internal belief), a is an action, r_t is immediate reward, s_{t+1} is the subsequent state, and $\gamma \in [0,1]$ controls the effective planning horizon.

This formulation makes explicit two structural properties not directly represented in static cue-based models. First, information-gathering actions can be valuable even without immediate reward, because they modify the agent's belief state and thereby influence future expected value. Second, navigation exhibits path dependence through belief evolution: each action reshapes both the external state and the internally maintained memory state, whose availability is governed by memory constraints.

Information Scent Information scent provides signals about which parts of the hierarchy are likely to contain the target. In our formulation, scent is not treated as a static local score, but as a memory-mediated representation that supports implicit inference over possible target locations.

Latent scent. In the environment, each option i is associated with a latent scent value $\hat{\psi}_i$, defined as the semantic similarity between the option label and the goal. We operationalize this similarity using pretrained sentence embeddings and cosine similarity:

$$\hat{\psi}_i = \frac{\mathbf{g} \cdot \mathbf{l}_i}{\|\mathbf{g}\| \, \|\mathbf{l}_i\|}.$$

This latent value represents the ground-truth cue strength available in the environment.

Noisy observation. Agents do not directly observe $\hat{\psi}_i$. Instead, scent becomes available only when an option is inspected, and the resulting observation is subject to perceptual uncertainty:

$$\tilde{\psi}_i \sim \mathcal{N}(\hat{\psi}_i, \sigma^2),$$

where σ captures limited precision in semantic judgment. This assumption is consistent with cognitive architectures such as ACT-R, in which cue activations are noisy (Anderson & Lebiere, 1998), and with resource-rational accounts that treat variability as arising from limited computational precision (Lieder & Griffiths, 2020).

Memory-mediated internal representation. Rather than maintaining an explicit Bayesian belief distribution, the agent integrates scent values with memory traces over past visits and selections. Uninspected options remain uninformative, while inspected options can contribute to the agent's internal representation only when they are memory-accessible.

Under this formulation, information scent influences behavior indirectly through a memory-mediated internal representation rather than as a direct decision variable. It does not directly enter the reward function, but shapes action selection by modulating the salience of candidate locations.

Memory Constraints We model memory constraints using two mechanisms: limited capacity and temporal decay.

Capacity limit. Working memory can actively maintain only a small number of items, typically around 3–5 (Cowan, 2001, 2010). Accordingly, at each step only a limited set of candidate options remains accessible for decision making. When more than K options satisfy $M_i(t) \geq \theta$, the agent retains the top-K items ranked by $M_i(t)$. This bottleneck enforces selective attention when multiple links appear plausible.

Temporal decay. Memory accessibility decreases with time and interference, producing robust recency and frequency effects (Anderson & Schooler, 1991). We model this through a decaying memory strength for each option i:

$$M_i(t) = e^{-\lambda \Delta k_i(t)} \left(b + a_s \hat{\psi}_i + a_v \sqrt{V_i(t)} + a_c \sqrt{C_i(t)} \right), \quad (2)$$

where $\Delta k_i(t)$ denotes the number of steps since the option was last encountered, $\hat{\psi}_i$ is its scent value, and $V_i(t)$ and $C_i(t)$ denote cumulative views and selections. The exponential term captures time-based forgetting, while additive components reflect cue diagnosticity and repetition. Only cues with $M_i(t) \geq \theta$ contribute to the belief state, as memory strength acts as a gating mechanism over available information. Consequently, memory influences behavior indirectly by constraining which cues enter the decision process, without affecting the reward function.

POMDP Formulation

We formalize hierarchical navigation as a Partially Observable Markov Decision Process (POMDP) $\mathcal{M} = \langle \mathcal{S}, \mathcal{A}, \mathcal{T}, O, R, \gamma \rangle$. This formulation captures three key properties of human navigation: (i) latent task structure, (ii) noisy and memory-constrained observations, and (iii) cost-sensitive sequential control.

State $\mathcal{S}$. The full state encodes the hierarchical structure, current location, navigation history, and the hidden target location. Crucially, the agent does not observe this state directly. Instead, decisions are made over an internal belief state constructed from partial and noisy information.

Actions $\mathcal{A}$. At each step the agent chooses among three operations: VISIT (inspect a candidate), SELECT (commit and descend), and RETURN (move up one level). These actions jointly capture exploration, commitment, and recovery in hierarchical search.

Observations O. Observations consist of noisy scent cues and memory-filtered evidence. When option i is inspected, the agent receives a stochastic scent estimate $\tilde{\psi}_i \sim \mathcal{N}(\hat{\psi}_i, \sigma^2)$. All observed cues are gated by memory strength $M_i(t)$ (Eq. 2); only cues with $M_i(t) \geq \theta$ remain accessible.

The observation at time t therefore includes: (i) currently visible options and their revealed scent values, and (ii) a limited set of previously encountered diagnostic cues retained in memory. This structure operationalizes information scent as belief evidence subject to forgetting and capacity constraints.

Transition $\mathcal{T}$. External state transitions follow the deterministic structure of the hierarchy: SELECT descends into a sublayer (or terminates if correct), RETURN ascends, and VISIT preserves depth while updating evidence. Although the hierarchical structure itself is deterministic, uncertainty arises at the level of belief updating: noisy perception and memory decay induce stochastic evolution of the internal decision state.

Reward R. The reward structure balances success and efficiency:

$$R_t = \begin{cases} +20 & \text{if the target is reached,} \\ -0.01 & \text{otherwise.} \end{cases}$$

The per-step penalty reflects opportunity cost, encouraging efficient search without prohibiting exploration. Backtracking is neither forced nor free; it emerges when belief uncertainty and memory decay reduce confidence in the current path.

Parameterization

We approximate the optimal policy using a policy-gradient reinforcement learning method in an episodic setting. The agent is trained on repeated navigation episodes in the hierarchical environment, optimizing expected cumulative reward under the specified cognitive constraints. Training continues until the average return stabilizes on a held-out validation set, indicating convergence of the learned policy. The same training procedure is used across all experimental conditions without additional tuning per condition. Cognitive parameters were restricted to empirically grounded ranges based on working-memory capacity (Cowan, 2001), forgetting dynamics (Anderson & Schooler, 1991; Schooler & Anderson, 2017), and perceptual variability in information scent (Pirolli & Card, 1999). Within these ranges, parameters were calibrated using Bayesian optimization to reproduce the qualitative direction and relative magnitude of observed human effects, rather than to optimize absolute performance. The model includes parameters governing memory capacity ($K = 4$), perceptual noise ($\sigma^2 = 0.08$), memory decay ($\lambda = \ln 2/5$), and memory update coefficients governing belief updating dynamics. To assess robustness, we perturbed each cognitive parameter by ±5%, ±10%, and ±25%. Aggregated sensitivity remained stable under 5% and 10% perturbations (M = 0.21) and increased moderately only at 25% (M = 0.26), with no qualitative reversals of the three target effects.

Evaluation Method

We evaluate whether the proposed account reproduces established qualitative effects in hierarchical navigation. Rather than replicating exact historical materials, we reconstruct experimental conditions that operationalize three well-documented environmental factors and compare directional trends with prior findings.

Task difficulty. Following Blackmon and Habuchi (Habuchi & Takeuchi, 2012), we instantiated three levels: *no-problem* (target link has a clear semantic advantage), *competing* (distractors with similarly strong cues), and *low-scent* (all links weakly related to the goal). Reported task items were used as anchors to align our instantiations with their operational definitions. For comparison, Habuchi et al. (Habuchi & Takeuchi, 2012) tested the same manipulation with 9 headings and 93 links derived from the Blackmon dataset, and found systematic increases in solution time and errors as difficulty increased.

Hierarchy depth. We compared a two-level 8×8 menu (64 options) with a three-level $4 \times 4 \times 4$ menu (also 64 options). This parallels Larson and Czerwinski (Larson & Czerwinski, 1998), who showed that deeper hierarchies increase solution time and disorientation. While their menus contained more total items, holding the choice-set size constant allows us to isolate the effect of depth.

Finally, we conduct ablations on sequential foresight (via γ) and on memory and noise components to assess their contribution to reproducing these qualitative effects.

Results

We evaluate whether the proposed resource-rational account reproduces established patterns of hierarchical navigation.

Emergent Trial-and-error navigation behaviors

The model consistently exhibits three core behaviors observed in human navigation.

Partial scanning. Across conditions, the number of inspections prior to the first SELECT action was smaller than the number of available items on the page, indicating non-exhaustive evaluation. In an 8-item layout, the first selection occurred after an average of $M = 3.36$ inspections ($SD = 1.45$), demonstrating that the agent commits before evaluating all alternatives.

Backtracking. Return actions occurred across conditions and increased systematically with uncertainty and structural complexity. Average return counts ranged from near zero in easy tasks to as high as seven in difficult or deep hierarchies, reflecting structured error recovery rather than undirected exploration.

Revisiting. Under high uncertainty or strong memory decay, previously inspected items were revisited. Revisit frequency increased markedly in low-scent and deep conditions, consistent with belief degradation and subsequent re-evaluation of earlier evidence.

Effect of task difficulty

Consistent with prior findings (Habuchi & Takeuchi, 2012), navigation cost increases monotonically from no-problem to competing to low-scent conditions.

In our simulations, average path length increased from approximately 11 steps in the no-problem condition to 18 in the competing condition and 27 in the low-scent condition (Figure 2 A). Click counts followed the same ordering.

Mechanistically, reduced scent discriminability increases belief uncertainty. Under competing or weak cues, multiple candidates retain similar posterior value, leading to exploratory loops, delayed commitment, and increased likelihood of memory decay. Thus, the difficulty effect follows from belief formation under perceptual noise rather than from explicit difficulty heuristics.

Effect of hierarchy depth

Replicating established findings (Larson & Czerwinski, 1998), deeper hierarchies produced longer trajectories and higher lostness compared to shallower structures with equivalent total options. The lostness score (Smith, 1996) is a standard metric of disorientation in hypertext navigation.

In our model, average path length approximately doubled when moving from a two-level (8×8) to a three-level (4×4×4) hierarchy (13.5 vs. 25.6 steps). Lostness likewise increased (0.19 vs. 0.28), indicating greater structural disorientation (Figure 2 B).

This effect arises from increased path dependence and memory interference. Deeper hierarchies require maintaining

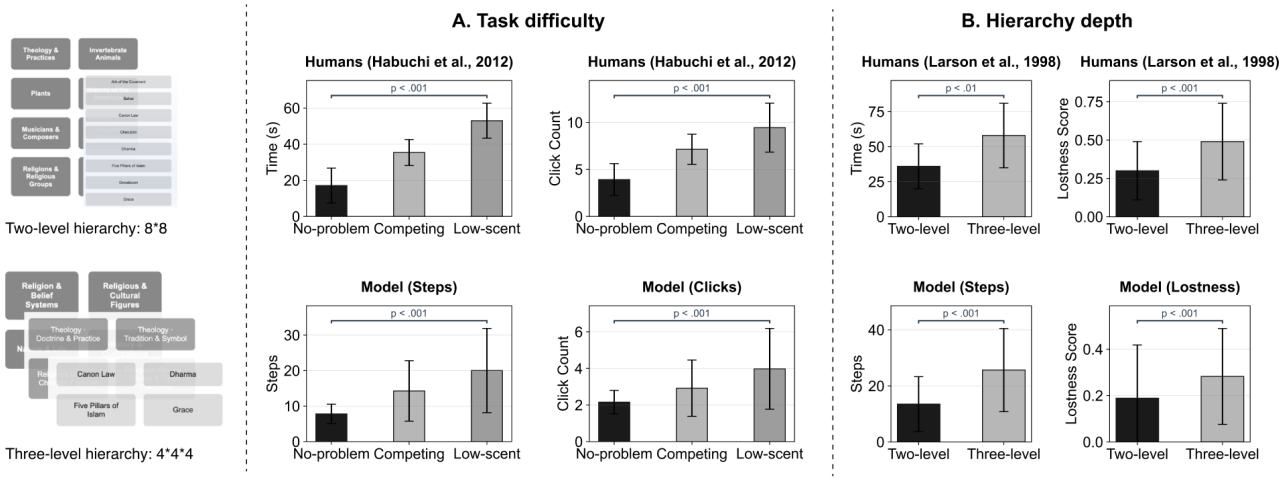


Figure 2: *Unified reproduction of three established navigation effects.* (A) Task difficulty: navigation cost increases from no-problem to competing to low-scent conditions. (B) Hierarchy depth: three-level structures produce higher cost and disorientation than two-level structures.

evidence across more sequential transitions, amplifying decay and increasing the likelihood of recovery behavior. Disorientation therefore follows from constrained belief maintenance rather than from structural depth alone.

Ablation study

Ablation: Effect of the Discount Factor γ The discount factor γ (Bellman equation 1) determines the effective planning horizon of the agent. Higher values emphasize long-term reward integration, whereas lower values induce myopic control. We compared $\gamma = 0.99$, $\gamma = 0.75$, and $\gamma = 0.50$.

As γ decreased from 0.99 to 0.75 and 0.50, navigation became increasingly myopic. Success dropped from 0.99 to 0.90 and 0.59, while path length increased from 12.10 steps ($SD = 9.57$) to 25.92 ($SD = 25.03$) and 43.15 ($SD = 32.70$). Lostness likewise rose from 0.47 to 3.17 and 6.41, and return actions increased from 0.71 ($SD = 2.68$) to 4.78 ($SD = 8.01$) and 9.69 ($SD = 12.30$). Lower γ also produced earlier and less accurate commitments: steps before first selection decreased from 4.64 ($SD = 1.65$) to 3.36 ($SD = 1.45$) and 1.00 ($SD = 0.00$), while first-selection success fell from 0.83 to 0.08 and 0.09. These results show that effective hierarchical navigation depends on long-horizon sequential control; when foresight is reduced, the agent commits prematurely and relies more heavily on trial-and-error recovery.

Ablation: effect of memory and noise components To assess the necessity of the proposed components, we removed memory decay and perceptual noise individually and measured the resulting trend similarity to human data.

The full model achieved a Δ-distance of 0.19. We define Δ-distance as a normalized change metric capturing the deviation between model predictions and observed human effects across difficulty and hierarchy conditions. Removing memory increased this to 0.32, while removing perceptual noise increased it to 0.39. Removing both components resulted in $\Delta = 0.35$.

Thus, eliminating either mechanism substantially degrades human–model alignment, indicating that both memory decay and stochastic scent perception are necessary to reproduce the qualitative structure of navigation behavior.

Discussion

This work proposes a resource-rational account of information scent in hierarchical navigation. We model navigation as sequential decision making over an uncertain belief state in an abstract POMDP sense, rather than as a sequence of locally optimal link choices. Within this framework, information scent is interpreted as a memory-mediated representation of observations under resource constraints, where decisions are based on uncertain observations of the target location, expected utility of actions, and the cost of further exploration.

Information Scent Theory (Pirolli & Card, 1999) characterizes navigation as information foraging: users follow cues that signal the expected value of a path. Architectural implementations such as SNIF-ACT (Fu & Pirolli, 2007) embed scent use within mechanisms like activation decay, retrieval noise, and production competition, and can account for sensitivity to cue strength and patterns of search efficiency. Our model builds on this perspective by representing information scent at the internal-state level. Instead of treating cognitive limits as purely architectural properties, we incorporate them as constraints in a sequential decision process. In our POMDP formulation, memory decay, observation noise, and limited foresight shape belief dynamics and influence navigation strategies.

This perspective provides a complementary interpretation of navigation behavior. Trial-and-error patterns such as revisiting and backtracking can be understood as emerging under uncertainty and cognitive constraints. Memory decay re-

duces the accessibility of previously acquired information, increasing the likelihood of revisiting information. Observation noise and competing cues sustain ambiguity among alternatives, making early decisions potentially reversible. Limited planning depth restricts the evaluation of long-term consequences, favoring myopic commitment to locally salient cues that may later be revised as new information is incorporated. These effects arise from a single underlying mechanism: regulation of a noisy, decaying internal state under limited foresight. The causal role of constraints is therefore explicit: increasing memory decay amplifies internal-state instability, increasing noise reduces scent discriminability, and shortening the planning horizon increases myopic commitments. Backtracking can thus arise when updated internal representations change the relative expected value of competing paths or when additional information alters prior evaluations.

This theoretical framing leads to distinctive predictions that are not naturally expressed by purely local scent-choice accounts. If scent directly determined action, the same visible links on a page should tend to produce the same choices. However, the same page can lead to different actions depending on prior evidence and memory state. A locally high-scent link may be rejected after failed exploration of its branch, because the belief that the target lies in that branch has decreased. Similarly, backtracking becomes valuable when the expected utility of continuing forward falls below the expected utility of returning to earlier alternatives. From a resource-rational perspective (Lieder & Griffiths, 2020), behavioral gradients across task difficulty and hierarchy depth therefore reflect adaptation within a bounded strategy space defined by computational limits, rather than post hoc deviations from an otherwise optimal local cue-following rule.

Several limitations remain. Future work should fit the model to trial-level human data, extend it to dynamic information spaces, and examine how it may be implemented in lower-level cognitive architectures.

In summary, this work recasts information scent as a memory-mediated, resource-rational process. By embedding scent within sequential belief dynamics under cognitive constraints, we provide a unified mechanistic explanation for why human navigation is systematically structured yet adaptively imperfect.

Acknowledgments

This work was supported by the European Research Council (ERC) Advanced Grant (No. 101141916) and the Research Council of Finland (grant numbers 328400, 345604, 341763, and 357578). X. Jin is further supported by the Alexander von Humboldt Foundation through a Humboldt Research Fellowship for Postdoctoral Researchers.

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