A Conceptual Framework for Digital Sensemaking as Semantic Trajectories in Web Environments

Nilupul Heshan Randika Kodikara, Umito Sorita, Nethmee Rasanga Gunasekara, Joy Karmoker, Junya Morita

Shizuoka University

nilupul.kodikara.23@shizuoka.ac.jp

Abstract

How do people construct coherent understanding while navigating information-rich digital environments? We address this question by modeling sensemaking as a trajectory through semantic space representing web navigation not as discrete page visits but as a continuous path through meaning. By analyzing the semantic content of web pages accessed during research tasks, we demonstrate that users' navigation patterns reveal two distinct forces: alignment toward task-relevant information and coherence with recently explored content. Statistical analysis showed that goal-directed alignment dominates information consumption, while motivational interest has negligible influence. This dissociation provides evidence that sensemaking operates as a distinct cognitive process, independent of intrinsic motivation. Temporal patterns in browsing behavior including how users maintain semantic coherence, drift from their goals, and accumulate meaning over time expose the hidden cognitive dynamics underlying knowledge construction. Our framework establishes semantic trajectories as a measurable phenomenon, bridging information foraging theory with modern computational models of meaning. This work reveals that the path users trace through information spaces reflects fundamental cognitive processes of interpretation and integration, offering new methods for studying how understanding emerges from interaction with complex digital environments.

Keywords: sensemaking; semantic analysis; meaning making; behavior analysis

1. Introduction

The contemporary digital environment presents learners and knowledge workers with continuous, heterogeneous streams of information competing for limited cognitive resources. This abundance has intensified what is characterized as an attention crisis, where maintaining goal-directed focus becomes increasingly difficult. Understanding how attention is guided through meaning-saturated digital environments thus represents a fundamental challenge for cognitive science, with implications for learning, decision-making, and human–computer interaction.

A key theoretical foundation for this challenge is Information Foraging Theory (Pirolli & CardPirolli & Card1999, Pirolli & CardPirolli & Card1999), in which individuals navigate information spaces by following local cues termed *information scent* that signal potential value prior to full engagement. Navigation, however, is not purely opportunistic; it also involves sensemaking, whereby encountered fragments are progressively integrated into coherent mental structures. This process is often narrative-driven, as users pursue evolving interpretive threads that link successive pieces of information. Digital navigation can therefore be understood as the construction of trajectories through meaning, shaped jointly by local cues and emerging interpretive context.

Representing such meaning-based trajectories requires appropriate semantic frameworks. Early approaches relied on structured networks (Collins & QuillianCollins & Quillian1969, Collins & QuillianCollins & Quillian1969) and lexical databases such as WordNet (MillerMiller1995, MillerMiller1995), treating semantic structure as fixed and symbolic. The distributional hypothesis (Bengio, Ducharme, Vincent & JauvinBengio .2003, Bengio, Ducharme, Vincent & JauvinBengio .2003) offered an alternative by grounding meaning in contextual usage patterns a view substantially advanced by deep learning–based embeddings, which represent words, sentences, and documents as vectors in high-dimensional spaces (KanervaKanerva2009, KanervaKanerva2009), enabling dynamic and quantitative computation of semantic relationships.

Building on these foundations, this study proposes a computational framework that models web-based sensemaking as a continuous trajectory through a shared semantic embedding space. By projecting visited content and task descriptions into this space, we quantify how users transition between related information, how semantic coherence is maintained across successive steps, and how navigation patterns evolve over time. Rather than treating browsing as a sequence of discrete page visits, our approach conceptualizes it as a structured process of meaning construction providing a principled computational window into the dynamics of sensemaking in complex digital environments.

2. Related Studies

Complex information activities involve an iterative interplay between exploratory search and sensemaking. Exploratory search describes navigation through multifaceted topics via cycles of querying, evaluating, and synthesizing (Kellar, Watters & ShepherdKellar .2007, Kellar, Watters & ShepherdKellar .2007), while sensemaking involves constructing external representations to reduce cognitive load and reveal cross-level connections. Notably, information gathering has been identified as the most cognitively demanding web-based task, as evidenced by time on task, windows opened, and pages visited (Kellar, Watters & ShepherdKellar .2007, Kellar, Watters & ShepherdKellar .2007).

Computational approaches to modeling sensemaking during web navigation remain limited. Because sensemaking is highly personalized, designing adaptive environments to support it is inherently difficult , and existing behavioral analyses ranging from sentence- to page-level granularity (Schraefel & ZhuSchraefel & Zhu2001, Schraefel & ZhuSchraefel & Zhu2001) consistently fail to capture the semantic continuity underlying navigation. Cognitive models of exploratory search have characterized it as a learning process (Juvina & van OostendorpJuvina & van Oostendorp2008, Juvina & van OostendorpJuvina& van Oostendorp2008), yet complex models often lack pragmatic applicability. What remains absent is a framework representing browsing not as a discrete sequence of page visits, but as a continuous trajectory through semantic space — one that reflects the coherence, progression, and dynamics of meaning-making across a session.

3. Method

This study investigated whether sensemaking during web-based information navigation can be operationalized as trajectories through semantic embedding space. A preliminary experiment examined browsing behavior during research tasks, with task interest manipulated as a within-subject factor to isolate semantic navigation dynamics from motivation-driven engagement.

3.1 Participants

The study involved eight participants, comprising five males and three females, aged between 24 and 29 years. All participants were postgraduate university students, albeit from diverse academic disciplines. They represented four distinct countries: India, Sri Lanka, Nepal, Bangladesh, and Myanmar. All participants are non-native speakers of English and are currently residing in Japan. The Experiment is conducted in English for all participants.

3.2 Materials

The study employed a dual-monitor setup, one for the web browser, one for task instructions and a timer with standard keyboard and mouse input. A customized browser extension logged mouse movements, scrolling, and visited page semantics at one-second intervals, transmitting data to a remote server for temporal alignment. Task materials consisted of university-level research prompts generated via ChatGPT-4.0 using a fixed prompt structure, ensuring semantic consistency across tasks while varying only topical content to isolate interest effects from linguistic confounds. A post-session questionnaire captured subjective ratings of task difficulty, familiarity, and engagement.

3.3 Experiment Procedure

Participants first completed an interest ranking task, ordering a list of university courses by personal interest; the highest- and lowest-ranked courses determined task assignment for the main session. In the main session, participants completed two 30-minute web-based research tasks on their selected topics, instructed to search for and bookmark relevant materials without composing a report. A brief questionnaire followed each task, and task order was counterbalanced to control for fatigue and order effects. Participants were encouraged to engage naturally and prioritize quality of information over quantity. Post-experiment questionnaires assessed task difficulty, topic familiarity, information satisfaction, and overall experience.

4. Analysis

4.1 Semantic Similarity Computation

This representation enabled the computation of two key similarity metrics capturing distinct aspects of navigation: *Task-Content Similarity* $Sim(T, C)$, which measures semantic alignment between the current page and the assigned task description, and *Previous-Current Similarity* $Sim(P, C)$, which measures alignment between consecutive page visits. While $Sim(T, C)$ reflects progress toward task goals, $Sim(P, C)$ reveals whether users maintain coherent semantic threads across successive steps. Visualized as time-series trajectories (Figure 3), divergence between these two metrics indicates semantic drift locally coherent exploration that progressively departs from task objectives.

4.2 Statistical Effects: Testing Goal-Directed vs. Interest-Driven Navigation

To test whether sensemaking operates independently of motivational interest, we conducted a 2×2 factorial ANOVA examining the effects of Semantic Relevance and Task Interest on information consumption. Each participant completed two tasks one high-interest and one low-interest. For each web resource, two semantic similarity scores were computed using the CLIP model: one against the task the resource was intended to support, and one against the foil task assigned to the same participant. This within-subjects baseline comparison controls for topic-general vocabulary overlap, ensuring that observed differences reflect genuine semantic alignment rather than superficial lexical matches. The two independent variables were **Semantic Relevance** (Relevant vs. Not Relevant), defined by whether the similarity

[b]0.40

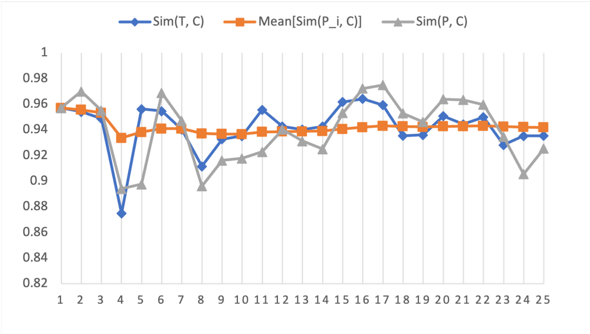

Figure 1 Graph A

[b]0.40

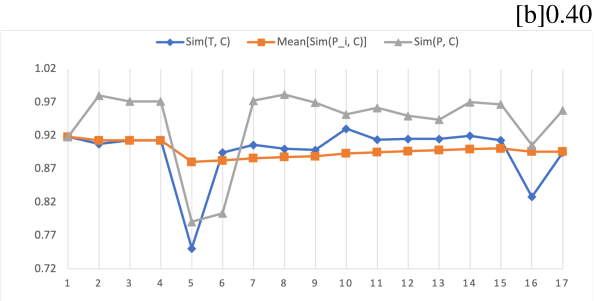

Figure 2 Graph B

Figure 3 Semantic similarity changing between task embeddings vs current web page embeddings $Sim(T, C)$, current web page embeddings vs previous web embeddings $Sim(P, C)$, and cumulative mean similarity of tasks and current web embeddings $Mean(Sim(P{-}i, C))$. The horizontal axis shows web resources in chronological order and the vertical axis shows similarity score.

score was computed against the associated task or foil task, and **Task Interest** (High vs. Low), based on participants' self-assessed topic preferences. The dependent variable was the semantic similarity score (range: 0–1). If sensemaking operates independently of motivational engagement, a main effect of Semantic Relevance would be expected with no significant interaction with Task Interest.

4.3 Trajectory-Based Analysis of Task Relevance and Semantic Drift

Although static similarity scores reveal whether motivational interest influences average semantic alignment, they do not capture how sensemaking unfolds over time. To examine these temporal dynamics, we extracted features from the $Sim(T, C)$ and $Sim(P, C)$ time series derived from the semantic similarity graphs (Figure 3), selecting 10 features based on coefficient-based feature importance. Using the same dataset as the prior experiment, we trained a Support Vector Machine (SVM) with a linear kernel ($C = 1.0$) on 73 samples (34 low-interest, 39 high-interest) to classify browsing sessions by interest level. Prior to training, features were standardized to zero mean and unit variance.

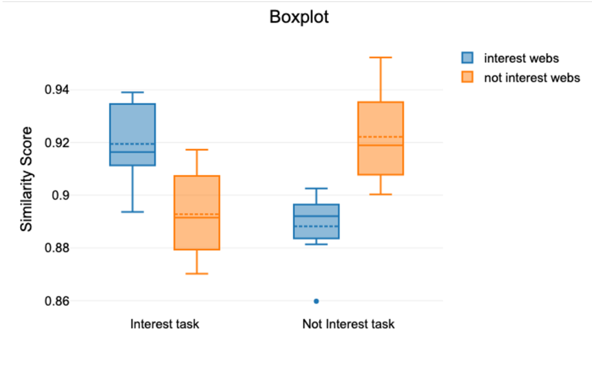

Figure 4 Semantic similarity scores between accessed web resources and task descriptions. The plot compares interest-relevant and not-relevant resources across high-interest and low-interest tasks, illustrating interaction effects between task interest and semantic relevance.

5. Results

We present two forms of evidence testing whether sensemaking during web-based information navigation can be operationalized as trajectories through semantic embedding space: first, statistical patterns in semantic alignment across task relevance and interest conditions; second, temporal trajectory patterns revealing how users navigate through conceptual space over time.

5.1 Semantic Alignment Across Relevance and Interest Conditions

Figure 4 displays semantic similarity scores across the four experimental conditions defined by Semantic Relevance (Relevant vs. Not Relevant) and Task Interest (High vs. Low). Materials semantically aligned with the assigned task (blue boxes) consistently show higher similarity scores than materials aligned with the task (orange boxes) across both interest conditions.

A 2 × 2 factorial ANOVA confirmed this pattern. Semantic Relevance showed a large effect, $F(1, 28) = 26.43$, $p < .001$, $\eta_p^2 = .49$, while Task Interest showed no detectable effect, $F(1, 28) = 0.02$, $p = .881$, $\eta_p^2 = 0$. The interaction was non-significant, $F(1, 28) = 0.39$, $p = .538$, $\eta_p^2 = .01$. Semantic Relevance accounted for 49% of the variance in similarity scores, while Task Interest showed no detectable effect.

5.2 Temporal Patterns in Semantic Trajectories

Figure 3 displays semantic similarity trajectories for a representative participant across high-interest (Graph A) and low-interest (Graph B) tasks. Each point represents a visited web page ordered chronologically. The blue line shows $Sim(T, C)$ (semantic alignment between the current page and task description), the gray line shows $Sim(P, C)$ (semantic alignment between the current page and the previously visited page), and the orange line shows the cumulative mean similarity.

Visual inspection reveals distinct patterns across interest conditions. In Graph A (high-interest task), both

$Sim(T,C)$ and $Sim(P,C)$ track closely throughout the session, with both metrics remaining relatively stable. In Graph B (low-interest task), $Sim(P,C)$ consistently exceeds $Sim(T,C)$, with the divergence between these metrics increasing over time. This pattern indicates that sequential similarity remains high while task similarity declines.

5.3 Classification of Trajectory Patterns

To examine whether temporal features extracted from semantic trajectories capture systematic differences across interest conditions, we trained a Support Vector Machine classifier on ten temporal features. The classifier distinguished between high-interest and low-interest browsing sessions using features including moving averages, cumulative sums, variability measures, and area under the curve for both $Sim(T,C)$ and $Sim(P,C)$ trajectories.

The classifier achieved 64.38% overall accuracy. Recall for the high-interest class (Class 1) was 74.36%, indicating that the model correctly identified approximately three-quarters of high-interest sessions. Precision for the same class was 64.44%.

6. Discussion

This paper is intended primarily as a conceptual contribution. The central theoretical claim is that sensemaking in digital environments should be modeled not only by whether users eventually reach relevant information, but by how meaning unfolds across successive steps of navigation (Maitlis, Vogus& LawrenceMaitlis.2013, Maitlis, Vogus & LawrenceMaitlis .2013; Hernes & ObstfeldHernes& Obstfeld2022, Hernes& ObstfeldHernes& Obstfeld2022; Brown, Stacey & NandhakumarBrown .2008, Brown, Stacey & NandhakumarBrown .2008). Representing visited pages and task descriptions in a shared semantic space makes that process observable: global task alignment ($Sim(T,C)$) captures movement toward an explicit goal, while local coherence ($Sim(P,C)$) captures continuity with the immediately preceding context. Together, these measures define a trajectory-based account of meaning construction that is closer to the theoretical view that understanding emerges through ongoing integration rather than isolated selections.

The present study should therefore be read as a proof of concept showing that sensemaking is feasible to operationalize with the current approach, rather than as a definitive process model. At the same time, this framing remains limited by the small and homogeneous sample, the page-level granularity of the trajectories, and the fact that semantic traces capture observable meaning construction but not reflective or phenomenological aspects of sensemaking. Increasing the number of trajectory measurements should make the characterization of sensemaking more profound, and future work should focus on converting this conceptual framework into a proper model with richer behavioral signals, larger samples, and stronger process-level validation.

7. Conclusion

The contribution of this work is primarily theoretical. Rather than proposing a predictive system or optimizing task performance, this study reconceptualizes sensemaking as a trajectory-relative process rather than an outcome-defined state. The empirical results serve not as definitive tests, but as a primary demonstration that semantic trajectories constitute a psychologically meaningful unit of analysis, in this case local semantic coherence and global goal-directed alignment capable of revealing more relative and descriptive patterns of meaning construction. In this sense, the proposed framework functions as a conceptual scaffold for future computational and cognitive models, constraining how sensemaking dynamics should be represented and studied.

References

bengio2003neuralBengio, Y., Ducharme, R., Vincent, P. & Jauvin, C. 2003. A neural probabilistic language model A neural probabilistic language model.. Journal of machine learning research3Feb1137–1155.

brown2008makingBrown, AD., Stacey, P. & Nandhakumar, J. 2008. Making sense of sensemaking narratives Making sense of sensemaking narratives.. Human relations6181035–1062.

collins1969retrievalCollins, AM. & Quillian, MR. 1969. Retrieval time from semantic memory Retrieval time from semantic memory.. Journal of verbal learning and verbal behavior82240–247.

hernes2022temporalHernes, T. & Obstfeld, D. 2022. A temporal narrative view of sensemaking A temporal narrative view of sensemaking.. Organization Theory3426317877221131585.

juvina2008modelingJuvina, I. & van Oostendorp, H. 2008. Modeling semantic and structural knowledge in web navigation Modeling semantic and structural knowledge in web navigation.. Discourse Processes454-5346–364.

kanerva2009hyperdimensionalKanerva, P. 2009. Hyperdimensional computing: An introduction to computing in distributed representation with high-dimensional random vectors Hyperdimensional computing: An introduction to computing in distributed representation with high-dimensional random vectors.. Cognitive computation12139–159.

kellar2007fieldKellar, M., Watters, C. & Shepherd, M. 2007. A field study characterizing Web-based information-seeking tasks A field study characterizing web-based information-seeking tasks.. Journal of the American Society for information science and technology587999–1018.

maitlis2013sensemakingMaitlis, S., Vogus, TJ.& Lawrence, TB. 2013. Sensemaking and emotion in organizations Sensemaking and emotion in organizations.. Organizational Psychology Review33222–247.

miller1995wordnetMiller, GA. 1995. WordNet: a lexical database for English Wordnet: a lexical database for english.. Communications of the ACM381139–41.

pirolli1999informationPirolli, P. & Card, S. 1999. Information foraging. Information foraging.. Psychological review1064643.

schraefel2001interactionSchraefel, M. & Zhu, Y. 2001. Interaction design for web-based, within-page collection making and management Interaction design for web-based, within-page collection making and management.. Proceedings of the 12th ACM Conference on Hypertext and Hypermedia Proceedings of the 12th acm conference on hypertext and hypermedia (pp. 125–125).