SHIZUOKA UNIVERSITY

MASTER THESIS

Developing a Mentoring System Based on Behavior Logging and Personalized Cognitive Modeling

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Declaration of Authorship

I, Nilupul Heshan Randika KODIKARA, declare that this thesis titled, "Developing a Mentoring System Based on Behavior Logging and Personalized Cognitive Modeling" and the work presented in it are my own. I confirm that:

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"Thanks to my solid academic training, today I can write hundreds of words on virtually any topic without possessing a shred of information, which is how I got a good job in journalism."

Dave Barry

SHIZUOKA UNIVERSITY

Abstract

Graduate School of Integrated Science and Technology
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Developing a Mentoring System Based on Behavior Logging and Personalized Cognitive Modeling

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This thesis presents a novel approach to real-time cognitive modeling and task performance prediction in digital learning environments by integrating semantic analysis, behavioral data, and machine learning. The proposed intelligent mentoring system is structured into three primary modules: (1) a Behavior Analysis Module, which combines semantic relevance estimation with interaction data such as mouse movements and scroll behavior to capture the learner's engagement context; (2) a Personalized Cognitive Modeling Module, which infers executive functions—including attention span, working memory, and susceptibility to distraction drawing inspiration from ACT-R architecture; and (3) a Predictive Machine Learning Module, which utilizes regression-based techniques to estimate current mental states and dynamically predict task completion time based on features extracted from the previous two modules. The main objective is to use behavioral and semantic cues to construct individualized cognitive models and predict task-related mental effort in real time. Time is treated as a dependent variable influenced by latent cognitive states, goal relevance, and motivational factors such as interest. In an experimental study with eight postgraduate students conducting web-based research tasks across varying interest domains, results showed that semantic alignment with learning objectives had a significant impact on information retrieval behavior, whereas user interest had no significant effect. A Support Vector Machine (SVM) classifier trained on semantic similarity features achieved an accuracy of 64.38% in distinguishing interest-relevant content. These findings suggest that goal relevance and cognitive state estimation, rather than interest alone, are critical for understanding and supporting learning behavior. This work contributes to the development of adaptive, cognitively-aware learning systems capable of delivering personalized interventions, optimizing task scheduling, and predicting learner performance based on real-time behavioral and semantic indicators.

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List of Abbreviations

TABLE 1: List of Abbreviations

ITS	**I**ntelligent **T**utoring **S**ystem
EEG	**E**lectro**E**ncephalo**G**raphy
ADHD	**A**ttention **D**eficit **H**yperactivity **D**isorder
CLIP	**C**ontrastive **L**anguage–**I**mage **P**retraining
SVM	**S**upport **V**ector **M**achine
AUC	**A**rea **U**nder the **C**urve
ANOVA	**A**nalysis **O**f **VA**riance
Sim(T,C)	**Sim**ilarity between **T**ask and **C**urrent content
Sim(P,C)	**Sim**ilarity between **P**revious and **C**urrent content

Chapter 1

Introduction

1.1 Background and Motivation

Web browsing plays a vital role in modern learning by enabling quick access to vast information. However, it also introduces a unique cognitive challenge: while users seek task-relevant content, they are simultaneously exposed to unrelated and potentially distracting materials. This dual nature of web interaction can disrupt focus and lower productivity, often beyond the user's conscious control.

One key concept that explains this loss of focus is "attention residue," which refers to the lingering cognitive effects of distraction that impair a person's ability to re-engage with the primary task. This phenomenon is shaped by various individual cognitive parameters, including attention span, working memory, emotional regulation, inhibition, and motivation. Understanding how these factors interact with user behavior and the semantics of the task at hand is essential for predicting performance in online environments.

Despite the complexity of these cognitive dynamics, traditional education systems often fail to accommodate them. Standardized, one-size-fits-all instructional methods, especially in self-directed online learning, frequently ignore cognitive and behavioral variability among learners (Zhao, Long, and Hu, 2022). As a result, a significant gap exists between current educational practices and the diverse learning needs of individuals.

1.1.1 Problem Statement

Despite the growing reliance on web-based environments for learning, current educational systems struggle to address the complex interplay between cognition and behavior. These systems often overlook how individual cognitive limitations—such as attention span, working memory, or susceptibility to distraction—directly influence learning behavior. Conversely, repeated behavioral patterns can, over time, reshape these very cognitive parameters, creating a dynamic and reciprocal relationship.

Superficial interventions like reminders, calendars, or time management apps are commonly used to support self-directed learning, but they often fail to engage with the underlying cognitive processes that drive behavior. Instead of manipulating external actions, what is needed are systems that promote metacognitive awareness by mirroring a learner's internal dynamics. Such systems can help individuals better understand how they learn, when they are distracted, and why their focus shifts.

Task completion time emerges as a critical measure of productivity in these contexts. While adequate time supports deep learning, excessive or misaligned time usage may reflect inefficiency, distraction, or cognitive fatigue. Therefore, time must be interpreted not just as a performance metric but as a window into internal cognitive states.

Multiple factors influence how long a learner engages with a task. These include mind-wandering, prior knowledge, task difficulty, motivation, interest, and even the semantic structure or complexity of the material being studied (Morita et al., 2020). Each of these factors contributes to how learners set short-term goals, manage attention, and experience distraction. Yet, many learning platforms fail to account for this variability, treating all users as cognitively uniform.

1.1.2 Research Objectives

This research proposes an intelligent mentoring system, following the tradition of intelligent tutoring systems (ITS) but focusing not on learning content but rather on organizing learning goals. The system aims to enhance web-based learning by considering executive functions of learners (Anderson, Boyle, et al., 1990; Aleven, 2010). By integrating cognitive modeling techniques, the system seeks to diagnose and support learners by identifying cognitive limitations, mitigating distractions, and improving overall learning efficiency.

The specific objectives include:

- Establish connections between behavior and internal cognitive dynamics to enhance bidirectional performance
- Develop a personalized dashboard that visualizes the alignment of internal dynamics with short- and long-term goals
- Lay the foundation for employing a cognitive architecture (e.g., ACT-R (Adaptive Control of Thought-Rational)), which is a widely used foundation for cognitive modeling to represent reading and information-seeking behavior (Anderson, Bothell, et al., 2004).
- Identify the feasibility of integrating a machine learning model that combines cognitive parameter estimations with semantic distraction metrics to construct a predictive model of task completion time and underlying cognitive influences

1.2 Significance of the Study

This research addresses the critical need for personalized educational approaches that bridge the gap between standardized methodologies and individualized learning needs. By establishing connections between behavior and internal cognitive dynamics, the system can provide meaningful interventions that enhance bidirectional performance. The qualitative and quantitative identification of cognitive profiles makes teaching and education more effective by providing educators with additional meta-knowledge about students. Task completion time serves as a key determinant of productivity, directly affecting the quality and efficiency of learning, making its accurate prediction valuable for educational optimization.

1.2.1 Scope and Limitations

The study focuses specifically on web-based learning environments and the cognitive factors that influence task completion during information-gathering phases.

The system concentrates on executive functions and cognitive parameters rather than learning content itself, following the tradition of intelligent tutoring systems but with a focus on organizing learning goals rather than delivering content.

The proposed system leverages behavioral data collected during web browsing to estimate the parameters of ACT-R, which is one of the most representative cognitive architectures. The scope includes the development of interventions tailored to individual cognitive profiles that can be used by mentors as additional guidance tools for understanding student learning patterns and needs.

1.3 Thesis Organization

This thesis is structured into six chapters that progressively build the research foundation, present the proposed system, and validate its effectiveness.

- **Chapter 1:** Introduces the research problem, objectives, and significance of developing intelligent mentoring systems for web-based learning.
- **Chapter 2:** Reviews related literature covering digital learning challenges, behavioral analysis techniques, and intelligent tutoring systems.
- **Chapter 3:** Presents the proposed system architecture, including behavioral logging, cognitive modeling, and prediction components.
- **Chapter 4:** Describes the experimental methodology, participant selection, materials, and data collection procedures.
- **Chapter 5:** Outlines the analytical procedures for processing behavioral and cognitive data.
- **Chapter 6:** Presents results including semantic relevance analysis, machine learning classification performance, and comparative framework discussion.

Chapter 2

Related Studies

This chapter surveys prior research to establish the theoretical and technological foundations of this study. It begins by examining digital learning environments, where cognitive challenges such as attention fragmentation and information overload shape user behavior. Building on this, the next section focuses on behavior analysis techniques used to capture learning processes in real time. Finally, the chapter reviews developments in intelligent tutoring systems (ITS). This progression from context to behavior to system modeling reflects the conceptual structure of the proposed approach.

2.1 Digital Learning Environments and Challenges

This section explores the cognitive and psychological dimensions of digital learning environments through four interconnected themes: attention and distraction management, information overload phenomena, applications of *cognitive load theory* which explains how the human brain processes and retains information under varying instructional conditions (Caldiroli et al., 2022), and relationship with time consciousness and *flow theory's* which describes describes a state of deep focus and immersion where individuals lose track of time, often achieved when challenge and skill are optimally balanced (Guoyao and Wenjie, 2020). As educational systems increasingly digitize, learners face environments that offer flexibility and vast information access while simultaneously demanding heightened self-regulation and cognitive control. Examining these core challenges illuminates the underlying mechanisms that shape learning effectiveness in technology-mediated contexts.

2.1.1 Attention and Distraction

General Attention Challenges in Digital Environments

The main challenge of the digital environment is preserving attention to the goal while engaging in the task (Closely related to the reflection in action concept in behavior science) (Iqbal, 2017). The various digital learning landscape presents varieties of unprecedented challenges to sustained attention and focus, fundamentally altering how students engage with educational content. Traditional classroom environments, while not without their distractions, provided more controlled settings where external stimuli could be managed more effectively. In contrast, digital learning environments expose students to a vast array of potential distractors, from social media notifications to multitasking opportunities across multiple digital platforms.

Cognitive science research reveals that attention regulation in digital contexts is profoundly influenced by interface design and multimodal feedback systems, with studies demonstrating a 32% reduction in distraction through optimized visual layouts. Research in educational technology reveals that the challenges of maintaining attention in digital contexts are particularly pronounced for certain populations. Studies examining social anxiety in digital learning environments have found that emotional and psychological factors significantly impact students' ability to maintain focus during online interactions (Ifenthaler et al., 2023). Female students, in particular, report higher levels of social anxiety in peer interactions within digital learning environments, which can lead to increased distraction and reduced engagement with learning materials (Ifenthaler et al., 2023). This gender disparity suggests that attention challenges in digital contexts are not merely technological but are deeply intertwined with social and psychological factors.

In addition to these general attention challenges, some learners experience more persistent and clinically significant difficulties due to cognitive disorders. These conditions—particularly ADHD require specialized attention strategies and adaptive systems to support sustained focus in digital environments. Addressing these needs is critical for designing inclusive learning systems that accommodate diverse cognitive profiles.

Cognitive Disorders and Adaptive Attention Interventions

Building on the broader discussion of attention regulation in digital environments, this section focuses specifically on how attention-related cognitive disorders such as ADHD (Attention Deficit Hyperactivity Disorder) influence learning processes and how adaptive interventions can support affected learners. Multi-modal interventions and high-stimulation digital environments have shown significant potential in supporting attention regulation among learners with ADHD. Multimodal intervention systems designed for ADHD learners employ real-time physiological feedback to achieve 81% accuracy in attention state classification (Andrikopoulos et al., 2024), thereby enabling just-in-time scaffolding through haptic notifications and content reconfiguration. Paradoxically, digital game-based learning environments demonstrate greater attentional sustainability among ADHD populations compared to neurotypical peers, suggesting inherent benefits of high-stimulation educational formats (Kim et al., 2023).

These findings collectively indicate that learners across various contexts frequently experience fragmented focus, where cognitive resources are divided between multiple stimuli simultaneously, a phenomenon known as *partial attention* (Rose, 2010). The phenomenon of continuous partial attention, first identified in digital workplace environments, has become increasingly relevant to educational settings. Students in digital learning environments often find themselves managing multiple information streams simultaneously, leading to divided attention that can compromise learning outcomes. This challenge is further exacerbated by the design of many digital learning platforms, which may not adequately consider the cognitive demands of sustained attention. The integration of artificial intelligence technologies, such as ChatGPT in metaverse learning environments, presents both opportunities and challenges for attention management (Al-Emran, 2024). While AI can provide personalized support that helps maintain engagement, it can also introduce additional complexity that may overwhelm students' attentional resources.

2.1.2 Information Overload in Web-Based Learning

The Nature and Scope of Information Overload

The overwhelming abundance of information in the digital age has created a paradox where increased access does not always translate into better learning, but can instead exacerbate challenges like partial attention and cognitive overload. This challenge of partial attention is further exacerbated by the digital age's unprecedented access to information, which has fundamentally transformed the educational landscape while simultaneously creating new challenges related to information management and processing. Web-based learning environments, while offering vast repositories of knowledge and diverse learning resources, can overwhelm students with the sheer volume of available information. This information abundance paradox suggests that having access to more information does not necessarily lead to better learning outcomes and may, in fact, hinder the learning process when not properly managed.

The challenge of information overload in web-based learning environments is not merely about the quantity of information but also the difficulty of discerning its quality and relevance. Students navigating digital learning environments must develop sophisticated information literacy skills to identify relevant, accurate, and useful content from the vast array of available resources. The bibliometric analysis of digital learning environments over three decades shows a consistent upward trend in research publications and technological developments (Saphira et al., 2023). This exponential growth in knowledge and tools, while beneficial for advancing the field, also contributes to the information overload challenge. In this case, it is increasingly difficult to make informed decisions about learning strategies and resource utilization.

Platform Proliferation and Management Challenges

Research examining the capabilities and challenges of digital learning during the COVID-19 pandemic revealed that while the availability of numerous digital learning platforms helped mitigate educational disruptions, it also created new challenges related to platform selection and information management (Yasir et al., 2022). Students and educators found themselves overwhelmed by the variety of available tools and resources, often struggling to identify the most appropriate platforms for their specific learning needs.

Digital concept mapping has emerged as one promising strategy for helping students organize and process complex information in online learning environments (Alt and Naamati-Schneider, 2021). Research on health management students' use of digital concept mapping in online courses demonstrates that structured approaches to information organization can support self-regulation and improve learning outcomes in digital contexts.

AI-Enhanced Solutions and New Complexities

The integration of artificial intelligence and machine learning technologies offers potential solutions for managing information overload in digital learning environments. AI-powered recommendation systems can help filter and prioritize information based on individual learning needs and preferences (Chaka, 2023)(Al-Emran, 2024). However, the implementation of such systems also raises concerns about algorithmic bias, information filtering bubbles, and the potential for over-reliance on automated systems for learning decisions.

While AI tutors can provide personalized support and reduce certain types of cognitive load, they may also introduce new forms of cognitive complexity related to human-AI interaction and information verification. The key lies in designing AI-enhanced learning environments that leverage the benefits of artificial intelligence while avoiding cognitive overload.

2.1.3 Flow theory and time consciousness

Temporal Perception and Flow State Mechanisms

Time consciousness in the digital environment faces so many challenges that we do not faced in offline learning. In virtual environments, the consciousness of time does not work in the way we think. The awareness of time can become distorted, leading learners to either underestimate or lose track of how much time has passed. A key factor influencing this phenomenon is the concept of flow state (Csikszentmihalyi, Abuhamdeh, and Nakamura, 2014), a mental condition in which individuals become fully immersed in a task, experiencing a deep sense of focus, reduced self-awareness, and an altered perception of time.

Managing flow states and temporal awareness requires sophisticated control mechanisms to optimize cognitive engagement and learning outcomes. Flow states are governed by complex neurological processes that involve reduced frontal cortex activity, allowing for enhanced implicit processing (Gold and Ciorciari, 2020). While EEG (electroencephalogram) based monitoring systems can track flow states in real time using alpha and theta band activity as primary indicators the challenge lies in creating systems robust enough to function reliably across diverse learning contexts and individual differences (Rácz et al., 2025). The relationship between time perception and flow states reveals critical control parameters that digital learning systems must navigate carefully. A study conducted by Rutrecht explore subjective experience of the time in the virtual reality gaming environment (Rutrecht et al., 2021). External clock-speed manipulation offers a direct method for controlling temporal perception, with research showing that altering clock tick duration can influence time monitoring behaviors and prospective memory performance (Laera et al., 2024). However, implementing such temporal control mechanisms in practical educational settings raises concerns about learners' ability to develop authentic time management skills and function effectively in non-manipulated temporal environments.

Individual Differences and Adaptive Control Systems

The challenge of accommodating individual differences represents one of the most significant obstacles in digital learning environment design. Neurodivergent populations require specialized flow control strategies that accommodate unique cognitive profiles, with individuals with ADHD potentially achieving flow in high-stimulation environments while those with autism spectrum conditions often require areas of deep personal interest (P. Hutson and J. Hutson, 2024). This diversity necessitates adaptive control systems capable of personalizing flow induction strategies, but current digital learning platforms lack the sophistication to provide such individualized approaches effectively.

Ethical Considerations and Educational Integration

The implementation of flow control technologies raises important ethical and pedagogical questions that must be addressed. The manipulation of cognitive states through technological intervention raises concerns about learner autonomy and the development of intrinsic motivation. Alkhresheh directly addresses cognitive state manipulation by using gamification to enhance cognitive abilities like concentration and memory (Al-khresheh, 2025). While controlled flow states may enhance immediate learning outcomes, there is a risk that learners may become dependent on technological assistance to achieve optimal learning states, potentially undermining their capacity for self-regulated learning ('t Veld and Nagenborg, 2019). The sophisticated monitoring required for effective flow control systems also raises privacy concerns related to the collection and use of neurological and physiological data (III and Ruotsalo, 2024). Digital learning environments incorporating flow control mechanisms must integrate with existing educational frameworks, assessment systems, and pedagogical approaches. Traditional educational structures often emphasize standardized timing, uniform pacing, and comparative assessment methods that may conflict with individualized flow control approaches (Wakeling and Robertson, 2017). The challenge extends to educator training and support systems, as teachers require new competencies to effectively implement flow control technologies and integrate them meaningfully into curriculum design. Addressing these challenges requires continued research into the temporal dynamics of flow state adaptation induced by sustained flow training.

2.2 Behavioral Analysis in Learning Systems

2.2.1 Browser Behavior Logging

Mouse interaction remains the primary interface between users and computer systems, particularly in educational and research environments where students predominantly use mouse-based navigation. The ubiquity of mouse usage in academic settings makes it an ideal modality for behavioral analysis in educational mentoring systems.

Recent research demonstrates sophisticated applications of mouse movement analysis for user experience evaluation and behavioral profiling (Souza et al., 2019). These studies reveal that mouse cursor movements contain rich information about user cognitive states, decision-making processes, and learning patterns, making them valuable for developing adaptive mentoring systems.

Mouse tracking technology enables the creation of individual profiles based on browsing patterns and interaction behaviors. While some studies identify privacy concerns related to user profiling through mouse cursor tracking (Souza et al., 2019), these findings have also led to the development of adversarial methods to mitigate unauthorized user profiling techniques. For educational mentoring applications, such behavioral profiling can be ethically applied to understand student learning patterns and provide personalized guidance.

The application of mouse tracking extends to cognitive research, where studies utilize mouse movement analysis to measure reaction times, processing stages, and response uncertainty. Particularly relevant is research examining how users evaluate health information on social media by mouse tracking (Lowry et al., 2022). Mouse tracking provided fine-grained insights into cognitive processing during information evaluation by capturing reaction time, decision dynamics, and uncertainty. Reaction times, measured as the duration from stimulus onset to response, were faster among participants with adequate health literacy, suggesting more fluent and intuitive processing of both statements and tweets.

Processing stages were examined using mouse trajectory metrics such as area under the curve (AUC) and horizontal deviation score (HDS), revealing predominantly unimodal distributions that indicate incremental information integration over time. Notably, approximately 25% of trials exhibited "cognitive overrides," in which participants reversed course late in the decision process—behavior consistent with dual-system processing models involving intuitive and deliberative components.

Response uncertainty was assessed via x-position flips, representing directional hesitations; higher x-flip counts among participants with inadequate health literacy pointed to greater decisional conflict and lower confidence. Collectively, these indicators—reaction time, trajectory curvature, and hesitation behavior—highlight how users typically evaluate information incrementally, while also showing that internal conflicts can prompt late-stage revisions. This multi-dimensional analysis demonstrates the power of mouse tracking in uncovering the temporal and dynamic structure of real-time decision-making.

This finding demonstrates that mouse tracking can capture real-time cognitive processing and predict internal brain dynamics, making it valuable for mentoring systems that need to assess student comprehension and engagement dynamically. The behavioral logs generated through mouse tracking thus provide a window into cognitive states that can inform adaptive educational interventions.

2.2.2 Biometric Approaches

Eye Gaze as a Window into Cognitive Processing

Eye gaze tracking offers a direct link between user behavior and internal cognitive processes, making it valuable for goal-oriented learning systems. It helps visualize how attention and focus align with short and long term goals, supporting the development of personalized dashboards that adapt to users' changing cognitive states and enhance learning performance.

Foundational research has established strong correlations between eye gaze patterns and neural activity, demonstrating that gaze behavior reflects underlying brain dynamics (Calder et al., 2002). This connection between observable behavior and cognitive processes provides the theoretical foundation for using gaze tracking in cognitive modeling for educational applications.

A critical question in multimodal behavior analysis concerns the relationship between different interaction modalities. Research examining the correlation between eye gaze and mouse movement patterns addresses this question directly (M. C. Chen, Anderson, and Sohn, 2001). This study demonstrates significant correlations between gaze and mouse movement patterns during reading tasks, suggesting that mouse behavior can serve as a proxy for attention and cognitive engagement when direct eye tracking is not feasible.

Even though eye gaze tracking has strong evidence in this study we did not use eye gaze because it has difficulty in using real-time learning environment. Since the proposed system has dynamic adjustment. it is not feasible to use eye-tracking devices.

Multimodal Integration for Cognitive Modeling

The convergence of findings from mouse tracking and eye gaze research indicates that behavioral logs can effectively predict internal brain dynamics and cognitive states (Hutt et al., 2016), which is fundamental for developing mentoring systems that adapt to individual learning patterns (Shareghi Najar, Mitrovic, and Neshatian, 2015). The correlation between observable behaviors and cognitive processes enables the development of computational models that can infer learning states, comprehension levels, and areas of difficulty in real-time. The integration of multiple behavioral modalities combining mouse tracking with gaze patterns and other behavioral indicators (Demšar and Çöltekin, 2017) offers the potential for more robust and accurate cognitive modeling in educational mentoring contexts, providing a comprehensive understanding of learner behavior and cognitive state for personalized educational support.

2.2.3 Semantic analysis techniques by behavior logging

There are couple of approches that have taken in this topic

Research into online behavior began early with studies by (Catledge and Pitkow, 1995; Montgomery and Faloutsos, 2001) examining web browsing patterns. While most work focused on single-site analysis using server logs, (Downey, Dumais, and Horvitz, 2007) developed state machine models for multi-site search behavior, and Park and Fader created statistical models for dual-site browsing.

This semantic analysis leads to detecting mental diseases like anxity (Silenzio et al., 2020). The paper analyzes user behavior logs from BioPortal, a repository of biomedical ontologies, to understand how users explore and interact with semantic resources on the web. It uses clustering and Markov chains to identify distinct browsing behavior types and characterize ontologies based on user interactions (Walk et al., 2016).

The paper focuses on formalizing user web browsing activity by mapping usage logs to domain ontology concepts, enabling semantic analysis. It uses temporalized description logics to query expressive patterns with semantic and temporal constraints. The approach is evaluated using logs from DBpedia and SWDF (Hoxha, Junghans, and Agarwal, 2012).

2.3 Intelligent Tutoring Systems (ITS)

2.3.1 Architecture and Modeling Foundations

ITS Loop Architecture and Mentoring Components

Modern ITSs operate through dual-loop architectures that facilitate comprehensive learner support. The outer loop determines the sequence of tasks or exercises a student should tackle next, basing its decisions on the student's historical knowledge and background. Concurrently, the inner loop focuses on monitoring a student's solution steps within a specific task, providing "appropriate pedagogical intervention such as feedback on a step, hints on the next step, assessment of knowledge and review of the solution" (Lindner, Krause, and Ramponi, 2022). These systems are fundamentally built upon models of domain knowledge, student characteristics, and pedagogical strategies. Incorporating mentors can have a significant effect on learning outcomes, as demonstrated by (Vapnik and Izmailov, 2016). Building on this concept (Huang and Z. Chen, 2016), addressed both mentor and learner perspectives by developing separate models for students, teachers, domains, and diagnosis.

Student Modeling Functions and Evolving Approaches

Central to any effective ITS is the student model, which serves as a comprehensive framework for storing and inferring aspects of a student's behavior and skills to inform tutoring decisions. The functionality of student models can be categorized into five distinct purposes: corrective (enables removing bugs in a student's knowledge), elaborative (fills in the student's incomplete knowledge), strategic (assists in adapting tutorial strategy based on student action and performance), diagnostic (assists in identifying errors in student knowledge), and predictive (assists in understanding student response to system actions), along with evaluative capabilities that assess overall student progress. The student model in Huang's work evaluates learners across cognitive abilities including memorizing, understanding, analysis, application, synthesis, and evaluation. While the teaching model plays a crucial role in interconnecting all other components, their approach places substantial emphasis on prior knowledge. Although they took a logical approach to mapping and understanding concepts, their framework lacks strong validation in incorporating actual human habits (Morita et al., 2022). Contemporary approaches to student modeling have evolved to encompass several sophisticated methodologies, each addressing specific aspects of learner representation and assessment.

2.3.2 Student Modeling Techniques

Knowledge Representation Models

The overlay model represents one of the most popular approaches, assuming that "student knowledge is a subset of domain knowledge". When student behavior deviates from the domain model, it is considered a knowledge gap requiring remediation. Modern overlay models employ qualitative measures such as good, average, and poor for knowledge level assessment, though they face limitations when students adopt alternative problem-solving approaches or harbor misconceptions not explicitly stored in domain knowledge. Constraint-Based Modeling (CBM) offers an alternative approach, evaluating student solutions against lists of relevant, satisfied, and violated constraints. This methodology, exemplified in systems like J-LATTE for Java programming, enables enhanced diagnostic accuracy through weighted constraint mechanisms. Bayesian Networks (BNs) provide another sophisticated modeling approach, employed in systems such as Andes for Newtonian physics and ACE for mathematical functions, which "carry out long-term knowledge assessment, plan recognition, and prediction of students' actions during problem solving".

Probabilistic and Semantic Approaches

Since attention to semantic content can significantly influence browser behavior, and browser behavior in turn varies depending on the nature of the semantic information consumed, we focus on the analysis of semantics. Bayesian Knowledge Tracing (BKT) has emerged as a widely adopted model that calculates "the probability that a student knows a skill at a given point in time based on their previous performance," incorporating parameters for "guess" (correct answer without knowing the skill) and "slip" (wrong answer despite knowing the skill) scenarios. Advanced probabilistic approaches include Knowledge Tracing Models (KTM) and Misconception Tracing Models (MTM), which leverage historical data and continually update to reflect evolving student behavior and skill levels. In contrast, our study employs prior semantics to detect human learning behavior patterns. One of the genuine challenges in Intelligent Tutoring Systems (ITS) is developing fully interactive support mechanisms (Brusilovsky and Peylo, 2003). This becomes particularly important when considering that during learning activities using ITS, receiving timely feedback from users' work is essential to detect possible learning problems at an early stage, thereby enabling appropriate teaching interventions (Durães et al., 2018).

2.3.3 Behavioral Modeling and Emerging Directions

Characterizing Student Behavior in ITS

Contemporary research has demonstrated the critical importance of characterizing diverse student behaviors within ITS environments. Help-seeking behaviors can be systematically categorized into "Help Abuse" patterns (such as "Ask Hint when Skilled Enough to Use Glossary" and "Glossary Abuse") and "Help Avoidance" behaviors (including "Try Unfamiliar Step Without Hint Use") (Meléndez-Armenta, Rebolledo-Méndez, and Huerta-Pacheco, 2022). Additionally, ITSs can detect and model off-task behavior and gaming the system strategies, such as rapid incorrect answer submissions to discover correct responses (Walkington and Bernacki, 2019). Student diligence, defined as "the domain-specific ability to maintain a high degree of focus on a given task within that domain," represents another crucial behavioral dimension influenced by self-control and self-efficacy. This construct can be measured through total time on task and total number of correct problems completed, with predictive models estimating diligence based on observable online behaviors. Furthermore, unsupervised clustering techniques can characterize learner behaviors and affective states, including boredom and engagement levels, during ITS interaction (Walkington and Bernacki, 2019).

LLMs, Semantic Analysis, and Predictive Modeling

Unlike traditional ITS that follow rigid, structured learning paths, our intelligent mentoring system operates at a meta-cognitive level by analyzing browsing behavior and semantic relevance during open-ended web exploration. Instead of directing content, it adaptively monitors natural information-seeking behavior to assess relevance to learning goals.

Large Language Models (LLMs) offer a new approach to simulating student behavior, including incorrect or uncertain responses using "hallucination tokens," helping distinguish misconceptions. However, the "Student Data Paradox" warns that relying on a single LLM for personalization can misrepresent diverse learner profiles, highlighting the need for multiple consistent models.

We align with (Uglev and Gavrilova, 2022), who emphasize combining semantic patterns and behavior logs for realistic learner simulation. (Guo and Agichtein, 2012) support this with a framework based on biometric behavior and machine learning. Recent models also predict student performance using course-agnostic features like ability metrics and response history, improving generalizability across domains.

Chapter 3

The System

3.1 System Overview

The intelligent mentoring system represents a paradigm shift from traditional one-size-fits-all educational approaches to a personalized, adaptive learning environment that considers individual cognitive differences and behavioral variations. The system's primary objective is to enhance web-based learning by leveraging real-time behavioral data and cognitive modeling to provide personalized *behavior representation* and interventions tailored to each learner's unique cognitive profile.

The system operates on the fundamental principle that *task completion time* (Rummel, 2020) serves as a crucial determinant of learning productivity and efficiency. By analyzing various cognitive and behavioral factors, including mind-wandering, prior knowledge, task difficulty, motivation, and interest levels, the system creates dynamic, individualized behavior representation (Kumar and Tomkins, 2010) that optimizes educational outcomes. The core innovation of this system lies in its dual-stage process of combining cognitive architecture and data analysis with machine learning. First, capturing semantic deviations (Lecue and Mehandjiev, 2010) during web navigation to infer behavioral patterns, and subsequently matching these patterns with corresponding cognitive profiles and psychometric assessments. This approach enables rapid, real-time generation of individualized cognitive parameter sets, allowing for precisely tailored learning interventions.

The system's architecture is designed to bridge the gap between standardized educational methodologies and individualized learning needs, fostering a more adaptive and effective online learning environment. Through continuous monitoring and analysis of user behavior, the system can predict task completion times, identify potential distractions, and proactively adjust learning schedules to maintain optimal engagement and productivity.

3.2 Architecture Components

The intelligent mentoring system comprises three interconnected modules that work synergistically to deliver personalized learning experiences. Figure 3.1 illustrates the comprehensive architecture and workflow, showcasing how these components integrate to create a cohesive system capable of real-time behavioral analysis and cognitive modeling.

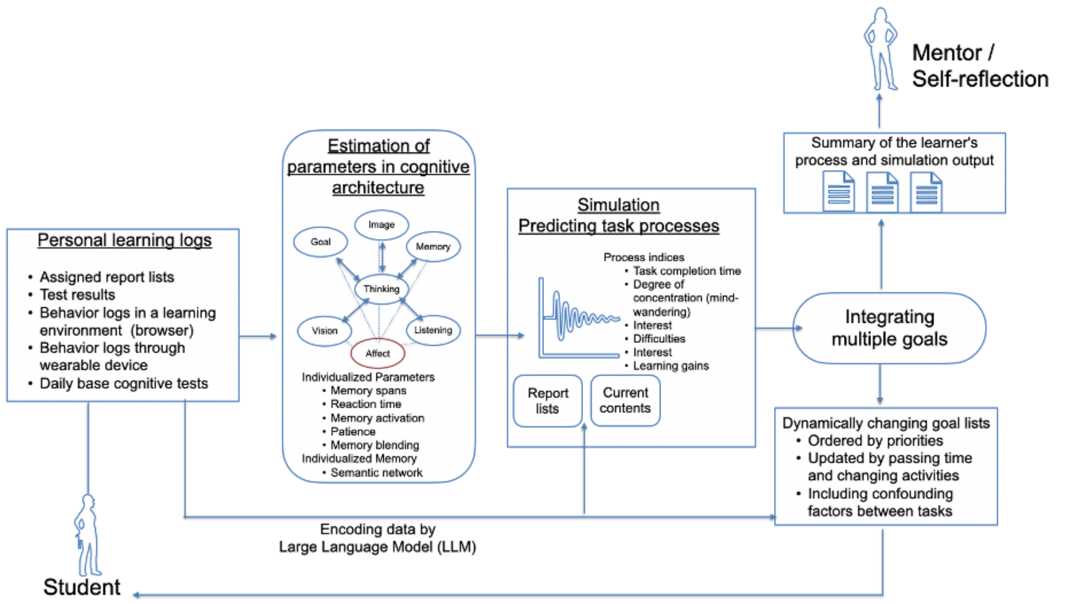

FIGURE 3.1: Comprehensive Architecture and Workflow of the System. This figure consists of several main components. (1) personalized learning log gathering (2) estimation of parameters in cognitive architecture, (3) simulation and prediction. integrating user goals with the system.

3.2.1 Behavioral Logging Module

The Behavioral Logging Module serves as the foundation of the system, responsible for capturing, analyzing, and interpreting user interactions during web-based learning activities. This module operates through a browser extension interface that provides real-time insights into user behavior while maintaining a non-intrusive learning environment.

Semantic and Behavior Log Analysis Engine

The Semantic and Behavior Log Analysis Engine constitutes the primary data collection and processing component of the behavioral logging module. This engine implements a comprehensive approach to understanding user engagement patterns through multi-dimensional data analysis.

Data Collection Framework:

We build a customized chrome extension that captures behavioral data through multiple channels, including mouse position, scrolling scroll position, web URL (web location), timestamps every 1 second. Each timelog have following structure and save as a json format.


```
{
  "logType": "REGULAR",
  "timeStamp": "2024-09-27T04:23:10.319Z",
  "scrolly": 0,
  "maxScroll": 991,
  "mouseX": 402,
  "mouseY": 235,
  "time": "1:23:10 PM",
  "date": "9/27/2024",
```

```
  "scrollTop": 0,
  "url": "https://www.google.com/"
}
```


Semantic Extraction and Analysis:

The system extracts semantic content from all accessed web resources in text-based format, creating a comprehensive repository of consumed materials which helps analysis. These semantics are grouped based on corresponding URLs and sorted chronologically according to user interaction timestamps. The semantic analysis employs the OpenAI CLIP (Li et al., 2021) model to convert the text into embeddings.

The engine implements a sophisticated relevance assessment mechanism that evaluates the semantic similarity between **task requirements** and **accessed content**. This assessment enables the system to categorize visited webpages as either task-relevant or unrelated content, providing crucial insights into user focus and potential distractions.

Pattern Recognition and Clustering Engine

The Pattern Recognition and Clustering Engine analyzes behavioral patterns to identify distinct user engagement strategies and cognitive states. This component focuses on detecting semantic drift patterns that indicate changes in user motivation, interest, and goal-setting behavior. This section incorporates various machine learning techniques to generate meaningful analyses for the subsequent components of the system.

3.2.2 Personalized Cognitive Module

Cognitive State Estimation and User Profiling

This is the second module of the pipeline, and it has the outputs of the previous module 3.2.1 as the base and primary inputs of this module.

We will leverage the ACT-R (Adaptive Control of Thought—Rational) because of the ability to make quantitative predictions and flexibility provide through the modular structure. ACT-R provides a detailed computational framework for understanding and simulating human cognition. It is based on the idea that the mind is composed of several independent modules that interact to produce intelligent behavior. Key components of ACT-R include a declarative memory (for facts and knowledge), a procedural memory (for skills and rules), and a set of buffers that hold information currently being processed. This structure helps us to leverage this technology for our study.

Cognitive Parameter Estimation & Behavioral Event Synchronization

This module focuses on estimating internal cognitive parameters, including working memory capacity, anxiety levels, and attention span, by integrating data from previously analyzed ACT-R models (Nagashima, Nishikawa, and Morita, 2024) and standardized psychological assessments to construct a user-specific ACT-R model tailored to individual cognitive characteristics (Weaver, 2008).

These behavioral events are synchronized with corresponding psychometric measures, such as memory assessments, attention tests, and anxiety scales, along with derived behavioral indicators like mind-wandering (Callard et al., 2013) which refers to thoughts drift away from what you're supposed to be focusing on. By aligning these datasets, it becomes possible to estimate individual internal states, representing cognitive constructs such as working memory load, attention control, and distraction susceptibility.

User-Specific reading & Cognitive Profile

These parameters are directly inferred from standardized psychological experiments and embedded into a user-specific cognitive profile. The cognitive profile serves as a foundation for personalizing the system's responses and interventions based on individual cognitive characteristics.

The main part of the cognitive modeling process will be the develop a new reading behavior model that replicates the user's reading dynamics. This additional model is informed by attention mechanisms and information foraging theory, allowing us to simulate how users navigate, select, and extract information during reading tasks. It acts as a complementary framework to better capture the attentional shifts and semantic search strategies employed by the user in real-world scenarios.

Simulation, Comparison, and Dynamic Adaptation

Furthermore, we utilize the cognitive model not only for profiling but also as a simulation engine to perform experiments that mirror those conducted by actual users. By comparing the simulated behavior from the cognitive model logs against real user logs obtained from the behavior logging module, discrepancies can be identified. When such mismatches occur, the system dynamically adjusts the cognitive model's parameters—such as memory decay rate, retrieval latency, or attention span—and re-runs the simulated experiment, iteratively refining the model.

This feedback loop enables dynamic calibration of the cognitive model based on user-specific behavioral changes over time. As a result, the module evolves in response to the user's current cognitive and behavioral state, allowing it to maintain higher fidelity in simulating, predicting, and supporting the user's learning process.

3.2.3 Simulation and Prediction Engine

Machine Learning-Based Feature Prediction

To predict task completion time, degree of concentration, interest level, difficulty assessment, and learning gain, we employ a machine learning approach that synthesizes behavior log analysis and cognitive modeling through regression models.

The proposed regression model integrates semantic analysis, online behavior, and cognitive parameters to personalize learning experiences. The model captures task-related content influence by analyzing web page embeddings, relevance scores, and interest levels.

Behavioral metrics including page visits, staying time, and mouse movements provide insights into attentional shifts and mind-wandering episodes. Cognitive assessments such as memory tests, attention span evaluations, and anxiety levels enable personalized predictions based on executive function limitations (Ritter, Tehranchi, and Oury, 2019; E. Nunez, Steyerberg, and J. Nunez, 2011; Pardoe, 2020).

Dynamic Learning Adaptation

These factors contribute to estimating memory span, attentional control, and cognitive load, which directly impact task performance. The regression model dynamically adjusts learning schedules by predicting task completion time as a function of user engagement and cognitive state, allowing for adaptive interventions and optimizing learning efficiency (Cen, Koedinger, and Junker, 2006).

This framework offers a scalable approach to personalizing learning interventions in dynamic educational technologies. The integration establishes robust mapping between user behavior and cognitive profiles, enabling accurate prediction of new users' behavior through real-time analysis of browser logs, interaction patterns, and semantic outputs.

3.2.4 Integration of Mentor

The intelligent mentoring system's integration with Large Language Models creates a transformative framework for mentors to provide personalized, data-driven guidance by leveraging real-time behavioral insights and cognitive profiling. By combining the Behavioral Logging Module's interaction data with the Personalized Cognitive Module's user-specific profiles, the LLM processes multi-dimensional learning patterns to generate contextually relevant recommendations, enabling mentors to identify cognitive overload, attention deficits, and conceptual struggles in real-time. The Simulation and Prediction Engine enhances this capability by forecasting performance outcomes and suggesting personalized learning pathways, allowing mentors to anticipate task completion times, difficulty levels, and potential obstacles before they manifest.

This integrated approach transforms traditional mentoring from reactive guidance to proactive intervention, where mentors can dynamically adjust task complexity, recommend semantically relevant materials, and optimize learning schedules based on individual cognitive states and behavioral patterns, ultimately creating a precision-guided educational experience that maintains human mentorship while maximizing learning efficiency through intelligent, adaptive support systems.

Chapter 4

Methodology

The objective of this research was to investigate the connection between web semantics, goal, and interest in the context of web-based information retrieval. This section presents a method to address the above objective by conducting browser base experiment with human participant and analyze the browser logs that capture during the experiment time.

4.1 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.

4.2 Materials

The materials of the study consist of:

- **Interest Rating Task:**
  - list of university courses to rank based on their interest levels.
- **Equipments:**
  - Monitor, which contains the web browser
  - Monitor to view task and timer
  - mouse
  - Keyboard
- **Data Collection Tool:**
  - Customized browser extension for logging user interactions(which can capture behaviors including mouse movements, scroll actions, and web page semantics).
  - A remote server which can record transmitted data at one-second intervals.
- **Task Generation:**

– Assignment prompts were generated using Large Language Models (LLMs), specifically ChatGPT (4.0) model (Prompts had a fixed structure, with topic content being the only variable).
– Questionnaire which participants have to complete after each task.

TABLE 4.1: Participant Course Rankings based on their interest to the courses

Course Name	**Rank**
Introduction to statistics	4
Multivariate analysis	12
Business management	7
Basics of computer networks	2
Algorithms and data structures	1
Data processing programming	6
Database theory	10
Basic information systems exercises	11
Web system design exercises	3
Informatics methodology	9
Management thinking	13
Cognitive science and behavioral information	5
Management design	15
Usability theory	8
Business planning	14
Data Analytics	1

4.3 Experiment Procedure

Participants followed a structured sequence of tasks, including an interest ranking task, a main task session, and post-task questionnaires. The experiment began with an interest ranking task, where participants ranked a list of university courses based on their interest levels (Table 4.1), with the highest-ranked courses and lowest-ranked courses determining the selection of assignments for the subsequent task phase.

After the interest ranking, participants were provided with the following instructions: *"Based on your rankings, we have created two assignments for you. Your task is to search the web for relevant materials that will assist you in writing an Answer report. Please remember that during the allotted time of 30 minutes, you should refrain from writing the report itself. Instead, focus solely on bookmarking any information you find useful for future reference. Feel free to act naturally without concern for evaluation."*

At the end of the instruction session, participants engaged in two 30-minute web-based research assignments on self-selected topics. They were instructed to search for and bookmark relevant information without composing a final report. A brief questionnaire followed each task, with an optional intermission. Participants were directed to evaluate webpage utility before bookmarking and to manage time efficiently. The study emphasized naturalistic engagement and quality of experience. Post-experiment questionnaires assessed task difficulty, topic familiarity, information satisfaction, and overall experience. This methodology facilitated the examination of cognitive fatigue, task interest, and semantic relevance in web-based learning and decision-making processes.

Chapter 5

Analysis

5.1 Data Collection and Processing

During the 30-minute task session, comprehensive behavioral and semantic data were collected from participants. The data collection process involved:

- **Semantic extraction:** All accessed web resources were processed to extract semantic content in text-based format.
- **Behavioral tracking:** Mouse movements, scrolling actions, and click activities were recorded at one-second intervals.
- **Temporal organization:** Extracted semantics were grouped by URL and sorted chronologically based on user interaction timestamps.

5.1.1 Semantic Content Extraction:

All web resources accessed by participants were subjected to rigorous semantic processing to extract meaningful textual content in a standardized format. To ensure consistency and accuracy across diverse web page structures, a manual text-capturing approach was employed. This method was chosen in preference to automated web scraping tools, which often apply inconsistent heuristics and selection criteria that may exclude relevant semantic information. By manually extracting the complete textual content from each web page, we ensured uniformity in the dataset and minimized potential bias introduced by tool-specific extraction behaviors.

5.1.2 High-Resolution Behavioral Tracking:

Participant interactions were recorded at one-second intervals, capturing mouse movements, scrolling, and clicks throughout the session. This high-resolution tracking enabled reconstruction of detailed behavioral trajectories, revealing patterns of engagement, attention shifts, and navigation behavior over time.

5.1.3 Temporal Data Organization and Synchronization:

The extracted semantic content was systematically organized using a sophisticated temporal framework that grouped materials by their corresponding URLs and sorted them chronologically based on precise user interaction timestamps. This temporal organization created a detailed timeline of information consumption that serves as the foundation for all subsequent analytical procedures. The synchronization process ensured that behavioral data and semantic content were precisely aligned, enabling integrated analysis of how behavioral patterns correspond to content characteristics and semantic relevance (Figure 5.1).

(A)

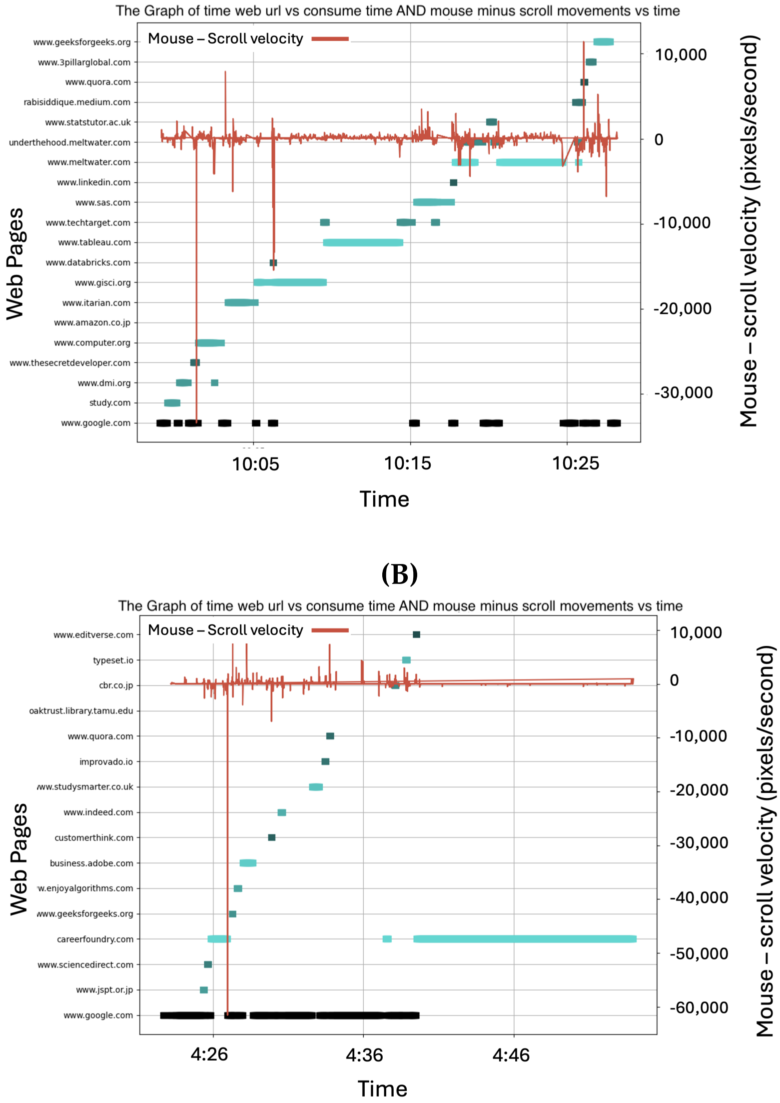

FIGURE 5.1: Navigation timeline of a participant in two different tasks with different interest levels. Graph (A) corresponds to high interest and familiarity, while graph (B) corresponds to low interest and familiarity. The horizontal axis shows time, and the vertical axis shows the domain name of the visited web URLs.

5.2 Semantic Similarity Analysis

5.2.1 CLIP Model Implementation

To assess the relevance of retrieved information, we employed the OpenAI CLIP (1.0) model to compare extracted semantics with predefined task descriptions. The CLIP model converts text into high-dimensional vector representations (embeddings) that capture semantic meaning, enabling quantification of conceptual similarity between different texts on a scale from 0 to 1, where higher values indicate greater semantic alignment.

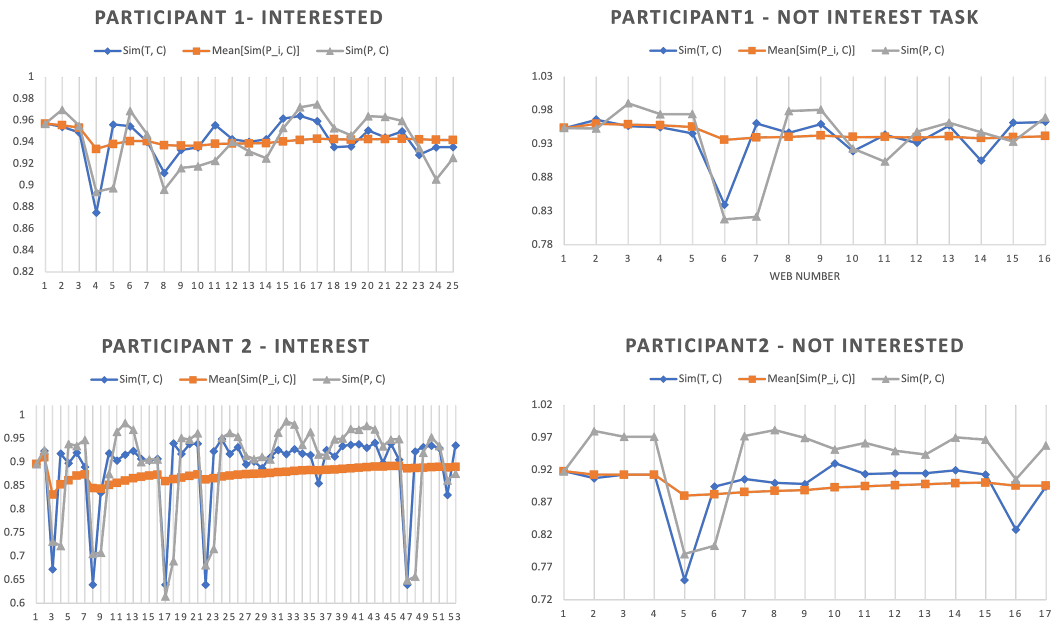

FIGURE 5.2: Semantic similarity changing between task embeddings vs current web page embeddings $Sim(T, C)$, current web page embeddings vs previous web embeddings $Sim(P, C)$, and cumulative mean similarity of tasks and current web embeddings $Mean(Sim(P - i, C))$. The horizontal axis shows web resources in chronological order and the vertical axis shows similarity score.

5.2.2 Comprehensive Similarity Metrics Framework

For each web resource, two key semantic similarity scores were computed:

1. **Sim**(T, C) **— Task-Content Similarity:** This metric quantifies the semantic alignment between the content of currently accessed web pages and the assigned task description. It represents how closely the accessed information aligns with the overall learning objectives and task requirements. High Sim(T, C) values indicate that users are accessing content that is directly relevant to their assigned learning goals, while lower values suggest exploration of tangential or unrelated materials.

2. **Sim**(P, C) **— Previous-Current Similarity:** This measure captures the semantic coherence between the content of the currently accessed webpage and the content of the most recently visited webpage. It provides insights into the

sequential logic of user browsing behavior, indicating whether learners are following coherent information-seeking strategies or engaging in more exploratory, divergent browsing patterns.

These similarity scores are visualized over time in Figure 5.2, which shows how the user's browsing aligns with task objectives and previous content, as well as the cumulative mean similarity trajectory. To evaluate semantic relevance, we compared each accessed web resource with both the assigned task description and the alternative task given to the same participant. This two-way comparison helped us identify whether a resource was truly relevant or only appeared so due to shared keywords or general topic similarity.

By using the alternative task as a baseline, we were able to set a clearer standard for what counts as meaningful similarity. If a web resource had high similarity with the assigned task and low similarity with the alternative task, it was considered semantically relevant. On the other hand, if it showed similar similarity scores for both tasks, it likely contained general information not specific to either task.

5.3 Statistical Analysis Framework

5.3.1 Two-Way ANOVA Design

A two-way analysis of variance (ANOVA) without repeated measures was conducted using data from 8 participants. Each participant completed two tasks: one aligned with a self-reported high-interest topic and another with a low-interest topic. The experimental design included two independent variables:

- **Task Interest** (High Interest vs. Low Interest), based on participants' prior self-assessed topic preferences.
- **Semantic Relevance** (Relevant vs. Not Relevant), defined by whether the similarity score was computed against the task the resource was associated with (Relevant) or the opposite task (Not Relevant).

Dependent Variable

The primary outcome measure was the *semantic similarity score*, a continuous variable reflecting the degree of semantic alignment between accessed web materials and task descriptions. These scores provide a quantitative assessment of content relevance, capturing subtle differences in semantic alignment beyond binary relevant/irrelevant classification.

The 2×2 factorial design allowed for a comprehensive assessment of the following effects:

- **Main effect of task interest:** Whether participants exhibit different information consumption patterns when engaged in high-interest versus low-interest tasks.
- **Main effect of semantic relevance:** Whether participants show a consistent preference for semantically relevant materials, regardless of their interest level.
- **Interaction effect:** Whether the influence of task interest on information consumption behavior depends on the semantic relevance of the materials accessed.

5.4 Behavioral Pattern Analysis

Beyond semantic analysis, the study incorporated an examination of online behavioral patterns, including mouse movements, scrolling activity, time spent on pages, and browser navigation sequences. All interaction logs and visited URLs were synchronized on a common timeline, enabling detailed analysis of user engagement across time.

Figure 5.1 shows that abstract visualization of the navigation pattern with the variation of mouse and scroll speed along with the time through materials. The horizontal green bars represent the duration of user engagement on each webpage; longer bars indicate more time spent, providing an intuitive visual cue for identifying where the user's attention was focused. The black bar indicates the search engine in this case, Google.com.

Larger and more frequent fluctuations in the red scroll velocity line are typically associated with skimming or skipping behavior, whereas smoother and more consistent patterns are more likely to reflect focused reading and sustained attention. This interpretation is strengthened by the observation that high scroll fluctuations often occur during shorter periods of content viewing, suggesting that users are not deeply engaging with the material. Additionally, users often switch rapidly between search engines and short-duration pages, which supports the assumption that they are quickly scanning content while actively searching for specific information.

5.5 Supervised Learning Approach

Given the limitations of traditional statistical approaches in capturing the dynamic, temporal nature of interest and engagement, our methodology incorporates a sophisticated supervised learning framework that operationalizes interest as a complex, multifaceted phenomenon that unfolds over time. This approach recognizes that interest cannot be adequately captured through static measurements but must be understood as a dynamic process that emerges through the interaction of multiple factors over time.

Theoretical Foundation

Our supervised learning approach is based on the understanding that interest is a comparative and temporal construct. It emerges from continuous evaluation of present experiences against prior interactions, expectations, and goals. These comparisons generate patterns in behavioral and semantic data that can be classified using machine learning.

Comprehensive Data Integration

The framework incorporates all accessed web materials to form a comprehensive dataset reflecting the full range of learning experiences. This inclusive design captures not only high-engagement moments but also low-interest and transitional states, providing a holistic view of interest dynamics.

Core Features

The classification system utilized two primary similarity measures:

- **Sim**(T, C)**:** Semantic similarity between the content of the currently accessed webpage and the assigned task description.
- **Sim**(P, C)**:** Semantic similarity between the content of the currently accessed webpage and the content of the most recently accessed webpage.

Derived Temporal Features

Through comprehensive analysis of semantic similarity trajectories, we developed a refined feature set capturing temporal dynamics and comparative relationships. These features were extracted from dual-trajectory data and refined through iterative feature selection.

Temporal Trend Features

- **Moving Average Sim**(P, C)**:** Captures local trends in sequential coherence, indicating whether users maintain consistent information-seeking strategies or shift between approaches.
- **Moving Average Sim**(T, C)**:** Reflects trends in task-focused behavior, showing whether users are becoming more or less focused on task-relevant information over time.

Accumulation Features

- **Cumulative Sum Sim**(T, C)**:** Represents total accumulated task-relevant information, indicating overall task engagement and learning progress.
- **Cumulative Sum Sim**(P, C)**:** Captures accumulated sequential coherence, reflecting the overall consistency of the user's browsing behavior.

Variability Features

- **Moving Standard Deviation Sim**(P, C)**:** Measures variability in sequential coherence, indicating stability or fluctuation in browsing patterns.
- **Moving Standard Deviation Sim**(T, C)**:** Assesses variability in task focus, revealing whether engagement is steady or fluctuating.

Area-Under-Curve (AUC) Features

- **AUC in Sim**(P, C)**:** Provides a comprehensive measure of sequential coherence throughout the learning session.
- **AUC in Sim**(T, C)**:** Offers an integrated measure of task relevance across the entire browsing session.

Depth and Magnitude Features

- **Depth Magnitude Sim**(T, C)**:** Captures the intensity of task engagement, identifying moments of deep, focused information processing.
- **Instantaneous Sim**(T, C)**:** Provides point-in-time assessments of task relevance to detect immediate interest shifts.

TABLE 5.1: Comprehensive Feature Categories and Descriptions for Supervised Learning Framework

Feature Category	Metric Name	Description	Type
Trend Analysis	Moving Average Sim(P,C)	Local trends in sequential coherence	Similarity Trend
Accumulation	Cumulative Sum Sim(T,C)	Total task-relevant information accessed	Similarity Accumulation
Variability	Moving Standard Deviation Sim(P,C)	Consistency of information-seeking strategies	Similarity Variability
Instantaneous	Sim(T,C)	Point-in-time task relevance	Instantaneous Similarity
Integration	AUC in Sim(P,C)	Comprehensive sequential coherence	Similarity Area (P,C)
Intensity	Depth Magnitude Sim(T,C)	Intensity of task-focused engagement	Similarity Depth
Variability	Moving Standard Deviation Sim(T,C)	Consistency of task focus	Similarity Variability
Integration	AUC in Sim(T,C)	Comprehensive task-focused behavior	Similarity Area (T,C)
Accumulation	Cumulative Sum Sim(P,C)	Total sequential coherence	Similarity Accumulation
Trend Analysis	Moving Average Sim(T,C)	Local trends in task focus	Similarity Trend

Two-Dimensional Visualization Framework

Our framework employs a two-dimensional visualization in which web materials are chronologically ordered by access time (x-axis) and plotted against semantic similarity scores (y-axis). Each accessed web resource generates two distinct data points corresponding to $\mathrm{Sim}(T, C)$ and $\mathrm{Sim}(P, C)$, forming dual trajectory lines. These trajectories reveal interest fluctuations through their comparative relationships over time.

Interest Classification Logic

The analytical power of the framework stems from comparative analysis between the two similarity trajectories across time:

- **Divergent trajectories:** When $\mathrm{Sim}(T, C)$ and $\mathrm{Sim}(P, C)$ values diverge significantly, it suggests a shift in interest or exploratory browsing behavior.
- **Aligned trajectories:** When the two similarity values align closely, it indicates sustained, task-focused engagement.
- **Temporal dynamics:** The evolving relationship between similarity measures provides insights into how user interest changes throughout the session, capturing nuanced attention patterns over time.

5.5.1 SVM-Based Interest Classification

Following the extraction and selection of key features that reflect the temporal and comparative nature of user interest, a supervised machine learning approach was adopted to operationalize the classification of user engagement. Specifically, a Support Vector Machine (SVM) was employed due to its effectiveness in handling high-dimensional feature spaces and its robustness to overfitting when properly regularized.

Dataset Preparation

A total of ten critical features were identified through systematic feature selection (as detailed in Table 5.1), each representing aspects of interest fluctuation through similarity trajectory divergence and temporal continuity. These features were computed from a dataset comprising 73 labeled samples derived from participant interaction data. The ground truth has two labels. Each web material accessed was classified as either *interesting* (39 samples) or *not-interesting* (34 samples), based on participants' self-reported interest levels on the subject topic before the experiment.

To ensure consistency across features and to preserve the integrity of comparative measurements, all features were standardized to have zero mean and unit variance. This preprocessing step was crucial in maintaining scale invariance, especially for the temporal derivative features that reflect the direction and magnitude of interest shifts across consecutive time points.

SVM Configuration and Training

The classification task was performed using an SVM model with a **linear kernel**, selected for its interpretability and suitability given the moderate sample size. The regularization parameter was set to $C = 1.0$, which balances the trade-off between maximizing the margin and minimizing classification errors.

The choice of a linear kernel was aligned with the conceptual framework of interest representation, where linear decision boundaries are sufficient to separate interest states when the features capture meaningful comparative and temporal structures. Each instance in the training dataset reflected a time-specific snapshot of user engagement, contextualized through the broader trajectory of similarity metrics.

Chapter 6

Results and Discussion

6.1 Semantic Relevance Analysis

6.1.1 Similarity Score Distributions

The effectiveness of the system was evaluated by comparing semantic similarity scores between accessed web resources and task descriptions. The similarity values between task-related semantics and the web resources consumed during the same task (relevant similarity) were compared with the similarity values between task-related semantics of the *other* task and the consumed web resources (non-relevant similarity). This analysis was conducted across both tasks for each participant.

As visualized in Figure 6.1, relevant documents (in blue) consistently exhibited higher similarity scores than non-relevant documents (in orange), across both high-interest and low-interest task conditions.

6.2 Interest vs. Relevance Analysis

6.2.1 ANOVA Results and Interpretation

A two-way analysis of variance (ANOVA) was performed to investigate the influence of relevance and interest on task completion, with similarity employed as the dependent variable. The results revealed no significant main effect of categorizing materials as interest or not-interest, $F(1, 28) = 0.02, p = .881, \eta_p^2 = 0$. However, there was a significant main effect of categorizing materials as relevant or not relevant to the goal, $F(1, 28) = 26.43, p < .001, \eta_p^2 = .49$. The interaction effect between task type and comparison type was not significant, $F(1, 28) = 0.39, p = .538, \eta_p^2 = .01$. These findings suggest that while relevance had a substantial impact on the outcome, accounting for 49% of the variance, neither interest nor the interaction between relevance and interest significantly influenced the results.

6.3 Machine Learning Classification Results

6.3.1 SVM Performance Metrics

Although the SVM classifier does not provide conclusive evidence, it shows potential for distinguishing between interest levels in consumed resources. The performance metrics were recorded in Table 6.1

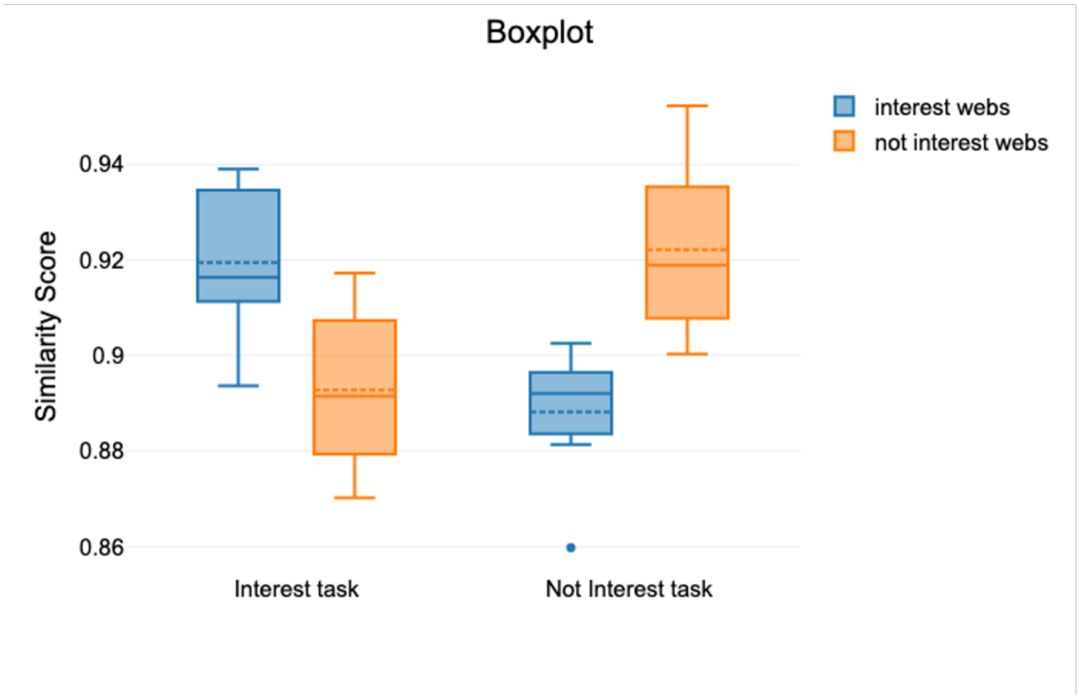

FIGURE 6.1: Boxplot of semantic similarity scores between accessed web resources and task descriptions. The plot compares interest-relevant and not-relevant resources across high-interest and low-interest tasks.

TABLE 6.1: SVM Model Performance

Metric	Value
Accuracy	64.38%
Precision (Class 1)	64.44%
Recall (Class 1)	74.36%
F1-Score (Class 1)	69.05%
Macro-Averaged Precision	64.37%
Macro-Averaged Recall	63.65%
Macro-Averaged F1-Score	63.56%

TABLE 6.2: Confusion Matrix for SVM Classification

Actual	Positive	Negative
Positive	29 (TP)	10 (FN)
Negative	16 (FP)	18 (TN)

6.3.2 Confusion Matrix Interpretation

6.3.3 Model Limitations and Improvements

Table 6.2 shows the confusion matrix on the SVM classification. The current model performance suggests moderate classification ability. However, the lack of robust accuracy indicates that interest detection through behavioral features needs further development. Future work will explore more reliable experimental designs and richer feature extraction approaches.

6.4 Discussion

The present investigation replicates naturalistic learning behaviors among students through the collection of high-resolution behavioral logs. While a related study by Magalhaes (Magalhães et al., 2020) employed a similar participant task structure, their approach incorporated controlled constraints to guide web search behavior. In contrast, the current study adopted a more naturalistic methodology by permitting participants to navigate the web freely, removing artificial restrictions to enhance ecological validity.

Although the study's analytical mechanisms demonstrated significant results in examining material relevance to short-term goals, interest measurement failed to yield significant findings through primary statistical analysis. Subsequently, we implemented Support Vector Machine (SVM) classification of web materials utilizing two-dimensional features comprising temporal and semantic similarity components. However, this analytical approach did not fulfill our initial expectations regarding classification accuracy.

To enhance classification precision, additional feature extraction appears necessary, as data quality may have influenced the outcomes. The task procedure itself may have affected data quality parameters, necessitating methodological refinements. Our current approach considers large temporal frames in semantic visualization graphs, where individual points on the x-axis represent total time consumed on specific websites. However, narrowing these temporal windows to more granular intervals, such as one minute or five seconds, would likely produce more accurate and smoother semantic graphs with enhanced temporal resolution.

The current analysis employs only two comparative trajectories for relative measurement: recent activity relative to current activity, and current activity relative to recent past activity. Expanding the analytical framework to incorporate additional semantic comparisons would potentially improve the robustness and accuracy of interest classification, suggesting that future implementations should consider multidimensional semantic relationship analysis to capture the full complexity of user engagement patterns.

Chapter 7

Conclusion

This study aims to achieve four primary goals: (1) to establish connections between user behavior and internal cognitive dynamics for improving bidirectional task performance, (2) to develop a personalized dashboard that visualizes the alignment between internal cognitive states and both short- and long-term goals, (3) to lay the foundation to employ the ACT-R cognitive architecture for estimating key cognitive parameters such as working memory capacity, attention span, and anxiety levels using behavioral web interaction data, and (4) Identify the feasibility to integrate a predictive machine learning model that combines cognitive estimations with semantic distraction metrics to improve the accuracy of task completion time prediction and to identify the internal dynamics influencing goal alignment.

Importantly, each individual has varied behavior on the browser, which can be meaningfully captured and analyzed by the behavior and semantic logs. These behavioral patterns hold potential for constructing personalized cognitive profiles for each user with the help of cognitive architecture. The constructed personalized model would be able to predict user internal dimensions and would have the ability to adjust based on changes in behavior.

Although the present results are limited by the lack of strong statistical validation due to constraints in task manipulation, the study provides a solid foundation for advancing techniques in detecting and interpreting individual learning behavior. In particular, while the implementation of ACT-R-based cognitive parameter estimation and the integration of predictive machine learning models were beyond the scope of this study, the current work lays essential groundwork for these future directions.

Future work will not only focus on refining classification models and advancing adaptive user modeling but also on leveraging machine learning techniques to examine the impact of cognitive limitations such as working memory constraints and attentional capacity on task completion time, within the framework of cognitive architectures. These developments aim to enhance the system's ability to support individualized learning pathways and improve both its predictive accuracy and generalizability across varied digital learning environments.

Appendix A

Example Materials which used for the analysis

A.1 Semantic Extraction

This section explains an end-to-end, reproducible pipeline to (1) collect all URLs visited during an experiment session, (2) extract full-page text from each URL (independent of the participant's scroll/consumption), and (3) compute text embeddings using CLIP's text encoder. These processes are repeated for every 30-minute browsing session.

A.1.1 URL collection

Every URL that user have visited during the experiment session. All the following content connected with this URL.

```
"url":"https://ja.wikipedia.org/wiki/%E3%83%87%E3%83%BC%E3%82%BF%E8%A7%
   A3%E6%9E%90"
```

A.1.2 Web Content extraction

All text content from the web pages was manually copied and extracted. following block represent that generate by the URL provided above. Following link will provide the full extracted content of 3 more URLs. After extracting every text we use CLIP model to convert those text into embeddings.

```
"content":"skip to main contentaccessibility help accessibility
   feedback python tutorial for data analysis all videos images
   shopping web news books more tools for beginners course free
   geeksforgeeks pdf github google sponsored python dashboards
   analytics monitor python with datadog datadog httpswww.datadoghq.
   com create realtime dashboards with datadog. get full visibility
   into python app performance. troubleshoot python app...."
```

A.1.3 Embeddings Generation

CLIP-based semantic similarity was computed by encoding both task descriptions and web content using the CLIP text encoder (openai/clip-vit-base-patch32). Texts exceeding the model's token limit were chunked and pooled to obtain fixed-size embeddings.

A.1.4 Similarity Calculation

We generate embedding from the CLIP and compare that embeddings with the task description embeddings using cosine similarity. This link contains sample similarity calculation data.

- Following data related with Interest Task session
- Calculating the Similarity score between the Task description that used in interest-task-session with the web materials that consumed in same session (noted as relevant in Chapter 5)
- Calculate the same web material with Task description that used in not-interest-task session (noted as not-relavent in Chapter 5)

```
"score":"Interest-Task Similarity = 0.9070, Not-Interest-Task
   Similarity = 0.8646",
```

A.2 Sample tasks that use in the experiment

Task description that generated under the topic which user have rated before. We use LLM to create these task descriptions.
Sample task: 1

```
Topic: Exploring Multivariate Analysis in Predictive Modeling Compose a
    detailed report (1200-1500 words) on how Multivariate Analysis
   techniques are applied in predictive modeling. Your report should
   address the following points: Introduction to Predictive Modeling
   and Multivariate Analysis: Define predictive modeling and explain
   how multivariate analysis supports the development of predictive
   models, especially in handling data with multiple variables. Common
    Techniques in Multivariate Predictive Modeling: Multiple
   Regression Analysis, Principal Component Regression (PCR), Partial
   Least Squares Regression (PLSR), Logistic Regression, Support
   Vector Machines (SVM). For each technique, briefly explain its
   purpose, the type of data it is suitable for, and how it
   contributes to making predictions. Applications in Various Fields:
   Research how multivariate analysis for predictive modeling is
   applied in fields such as finance (e.g., stock market predictions),
    healthcare (e.g., disease diagnosis), and marketing (e.g.,
   customer behavior forecasting). Include specific examples from
   studies or case analyses. Evaluation of Model Performance: Describe
    key metrics used to evaluate the performance of predictive models
   created through multivariate analysis, such as R-squared, RMSE, and
    AUC-ROC. Conclusion: Summarize the effectiveness and limitations
   of multivariate analysis in predictive modeling, and suggest areas
   for future improvements in the field.
```

Sample task: 2

```
Introduction to Management Design: Define management design and explain
    why it is critical in shaping organizational success, focusing on
   how it influences communication, decision-making, and resource
   allocation. Core Principles of Management Design: Describe key
   principles such as strategic alignment, adaptability, collaboration
   , and innovation. Explain how these principles are applied in
   structuring an organization. Frameworks and Models of Management
   Design: Mintzberg's Organizational Configurations. The McKinsey 7-S
    Framework. Balanced Scorecard. Design Thinking in Management. For
   each framework, describe its main components, purpose, and the
   types of organizations or contexts it is best suited for. Case
   Studies in Management Design: Research two real-world companies (e.
   g., Apple, Google, Toyota) and analyze how they implement
   management design principles and frameworks to achieve strategic
   goals. Highlight specific structural or design changes they made
   and the outcomes. Conclusion: Summarize the importance of effective
    management design, and suggest emerging trends or future
   directions for management design in adapting to new challenges (e.g
   ., remote work, digital transformation).
```

Sample task: 3

```
Write a 1500-word research paper on the role of advanced chemistry in
   solving engineering problems. Focus on real-world applications and
   chemical principles. Address the following sections: Introduction
   to Advanced Chemistry in Engineering. Define advanced chemistry and
    its significance in engineering fields. Explain how chemical
   principles support engineering innovations. Chemical Reactions in
   Engineering ProcessesDiscuss two major types of chemical reactions
   commonly used in . engineering (e.g., catalytic reactions,
   polymerization, or electrochemical reactions). Provide industrial
   examples where these reactions are essential. Material Synthesis
   and Engineering Applications. Explain the process of synthesizing
   two advanced materials (e.g., composites, nanomaterials, or
   semiconductors). Highlight their engineering applications and
   performance benefits. Case Study: Chemical Engineering Innovation.
   Choose a real-world chemical engineering project (e.g., sustainable
    fuel production, water purification, or battery technology).
   Describe how advanced chemistry principles were applied to solve
   engineering challenges. Environmental and Sustainability
   Considerations. Discuss the environmental impact of chemical
   processes in engineering. Explore emerging green chemistry
   practices and sustainability innovations.
```

Sample task: 4

```
Write a 1500-word research paper on the role of nanomaterials in the development and performance of single electron devices (SEDs). Address the following sections: Introduction to Nanomaterials and SEDs. Define nanomaterials and single electron devices. Explain why nanomaterials are critical for the development of SEDs. Properties of Nanomaterials. Discuss three key properties of nanomaterials (e.g., quantum confinement, electrical conductivity, and surface-to-volume ratio). Explain how these properties make nanomaterials suitable for SEDs. Fabrication Methods. Describe two fabrication techniques used in producing nanomaterials for SEDs (e.g., chemical vapor deposition, molecular beam epitaxy). Include an overview of the processes and challenges involved. Applications of SEDs. Explore two practical applications of single electron devices (e.g., quantum computing, ultra-low-power electronics). Provide real-world examples of projects or prototypes using SED technology. Challenges and Solutions. Identify two key challenges in integrating nanomaterials into SEDs (e.g., stability, scalability). Discuss proposed solutions or current research aimed at overcoming these challenges.
```

A.3 Sample web transition for browsing session

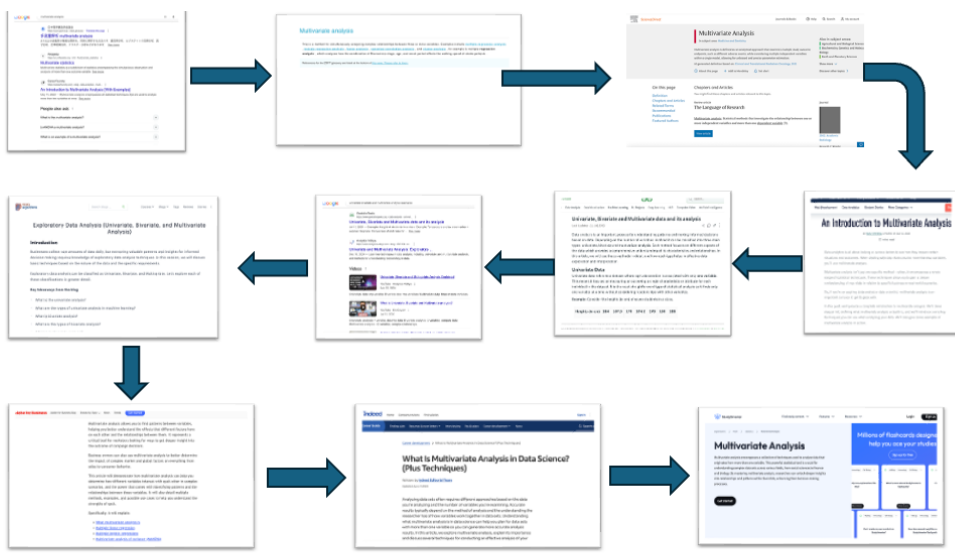

FIGURE A.1: The web page transition in the experiment session denoted in Figure 5.1-(B)

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