Learning Analytics and Generative AI: Mapping Cognitive Engagement in Nursing Education

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Abstract

Recent advances in artificial intelligence have created new opportunities for nursing education, yet empirical understanding of how nursing students engage with AI-enhanced learning environments remains limited. This study proposes to examine student engagement patterns within Sherpath AI, an advanced generative AI chat tool powered by trusted Elsevier content. Using Chi and Wylie's (2014) Interactive, Constructive, Active, Passive (ICAP) framework as its theoretical foundation, this research will analyze how different modes of student engagement correlate with learning outcomes. Through a mixed-methods approach combining learning analytics with qualitative analysis, the study will examine chat logs, system interaction data, and learning outcomes across three phases: development of analytics framework, data collection and primary analysis, and pattern analysis. Expected outcomes include understanding the distribution of ICAP engagement modes, their relationship to learning performance, and identification of effective engagement patterns. This research will contribute to both learning analytics and nursing education by providing a theory-driven framework for analyzing AI-supported learning interactions and developing evidence-based guidelines for implementation.

Keywords

Nursing education, learning analytics, ICAP, generative AI, student engagement

1. Introduction

Recent advances in artificial intelligence have spurred cautious optimism in nursing education delivery and student learning processes [1]. While preliminary evidence suggests readiness among nursing students to use AI-enhanced learning environments [2] there remains limited empirical understanding of how nursing students engage with these systems and how varying engagement patterns influence learning outcomes. This research gap is particularly significant given the complexity of nursing education, where students must develop not only content knowledge but also clinical reasoning and critical thinking skills [3].

This proposal outlines a plan to examine logs of student interactions with Sherpath AI (SPAI), an advanced generative AI chat tool designed for nursing education. Through application of the Interactive, Constructive, Active, Passive (ICAP) theoretical framework [4], this study aims to analyze how different modes of student engagement correlate with learning outcomes and to develop evidence-based guidelines for optimizing AI-supported learning in nursing education.

2. Relevant Literature

Learning analytics presents opportunities for understanding student engagement patterns in digital learning environments, with recent research demonstrating how meaningful insights can be derived even from small datasets [5]. This methodological advancement is particularly relevant for studying AI-enhanced learning tools in nursing education, where cohort sizes may be limited but the need to understand engagement patterns remains crucial. Despite these opportunities, the field of learning

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analytics faces important theoretical challenges. Current analytics frameworks often lack grounding in educational theory [6], and research connecting analytics insights to pedagogical practice remains underdeveloped [7]. This theoretical gap limits our ability to derive meaningful pedagogical insights from learning analytics data, particularly in complex educational contexts like nursing education where multiple learning objectives must be achieved simultaneously.

The Interactive, Constructive, Active, Passive (ICAP) framework provides a structured theoretical foundation for examining these engagement patterns, offering well-defined categories for classifying different modes of cognitive engagement and their relationship to learning outcomes [4]. Recent research by Lim et al. [8] underscored the efficacy of the ICAP framework in promoting deeper learning through interactive engagement, demonstrating that preparatory activities such as self-study and question generation significantly enhanced post-test performance in health professions education. These findings highlight the value of integrating active and constructive engagement strategies into AI-supported learning environments. Stout and Smith [9] further illustrated the potential of ICAP-guided approach in veterinary nursing education, integrating real-world workplace challenges into interactive modules. Their work emphasized the importance of designing educational interventions that build cognitive and practical skills through engagement modes tailored to professional contexts.

This framework's emphasis on observable learning behaviors makes it particularly suitable for analyzing student interactions with AI-supported learning tools, where engagement patterns can be systematically tracked and analyzed. As such, the driving questions of this research agenda are, *'How do nursing students' interactions with Sherpath AI align with the ICAP framework's modes of cognitive engagement? (RQ1) What relationships exist between ICAP-classified engagement patterns and measurable learning outcomes? (RQ2) and, How can we support nursing students in developing more effective AI-learning interactions? (RQ3).*

3. Theoretical Framework

This investigation employs the ICAP framework [4] as its theoretical foundation, positing those different modes of cognitive engagement correlate with varying levels of learning outcomes. The framework was selected for its ability to classify observable learning behaviors, making it particularly suitable for analyzing digital learning interactions. In the context of AI-supported learning environments such as Sherpath AI (SPAI), the ICAP modes may manifest and be examined in ways operationalized in Table 1.

Table 1
Operationalization of ICAP Modes in AI-Supported Learning

Mode Characteristics	Passive Engagement	Active Engagement	Constructive Engagement	Interactive Engagement
Student Behavior	Students passively consume information (e.g., reading responses from SPAI without follow-up questions)	Students take an active role (e.g., asking straightforward questions)	Students engage constructively (e.g., brainstorming care plans or seeking rationales for deeper understanding)	Students engage in back-and-forth interactions with SPAI, simulating a dialogic learning process
Cognitive Process	Characterized by receptive behaviors without	Involves direct manipulation of	Requires generation of novel content	Characterized by substantive dialogue and

	overt content manipulation	learning materials	beyond presented materials	knowledge co-construction
Observable Action	Time spent viewing SPAI responses without follow-up interactions, Duration of content viewing sessions without active engagement, Single view patterns where students read but do not interact, Time gaps between SPAI responses and student actions	Basic content clarification requests, Simple definition queries, Direct fact-checking questions, Navigation between different content areas, Basic prompt reformations	Synthesis of information across multiple topics, Self-generated examples or applications of concepts, Extended responses demonstrating reasoning, Novel questions connect multiple concepts, Creation of own scenarios of case examples	Multi-turn exchanges with progressive complexity, Building upon previous responses in the same conversation, Sequential question-answer patterns showing deeper inquiry, Conversations with multiple related but distinct queries, Follow-up questions that reference previous answers
Measurement Approach	Measured through view times and basic interaction logs	Quantified through interaction frequency and duration metrics	Assessed through content analysis of student generated materials	Evaluated through dialogue analysis and response patterns

4. Methods

4.1. Sherpath AI (SPAI)

Sherpath AI combines evidence-based nursing content with generative AI capabilities, enabling: (a) Real-time student support through natural language dialogue, (b) Practice question generation and feedback, (c) Clinical reasoning development through case discussions, and (d) Self-directed learning pathways. Students primarily interact with the system through: (a) Content queries and clarification requests, (b) Practice question generation, (c) Clinical case discussions and care planning and (d) Concept exploration and synthesis. The system generates detailed interaction logs including timestamped chat messages, activity completion records, system feature usage patterns, session duration and frequency data.

4.2. Research Design

This study will employ a mixed-methods approach combining learning analytics with qualitative analysis of student-SPAI interactions. The research design will unfold in three distinct phases, each building upon the previous one to develop a comprehensive understanding of student engagement patterns and their relationship to learning outcomes (see Table 2).

Phase 1 will focus on developing the analytics framework. This initial phase encompasses three key components: First, the development of the ICAP classification framework, including creating classification schemes for each mode, developing natural language processing (NLP) algorithms for engagement pattern identification, and establishing classification rules. Second, a validation process incorporating expert review of classification criteria, pilot testing with sample interaction data, and refinement of algorithms. Third, reliability assessment through inter-rater reliability testing, cross-validation of automated classification, and establishment of quality metrics.

Phase 2 will involve data collection and primary analysis. This phase begins with systematic collection of SPAI interaction logs, including chat dialogue transcripts, activity completion patterns, system feature usage data, and session metrics. Course performance data, including examination scores (e.g., HESI Specialty Exam) will also be collected. The ICAP classification framework will be implemented through automated categorization of engagement patterns, with manual validation and refinement of classification criteria. Preliminary analysis will include sequential pattern mining of engagement sequences, analysis of transition patterns between ICAP modes, and initial correlation analysis with learning outcomes.

Phase 3 will focus on integration and pattern analysis. This phase involves comprehensive analysis of engagement patterns across ICAP modes, investigating relationships between engagement patterns and learning outcomes, and examining temporal aspects of engagement. Pattern validation includes expert review, validation against learning outcomes, and cross-validation across student cohorts. The phase concludes with model development, including creation of predictive models and development of guidelines for optimal engagement.

Table 2
Operationalization of ICAP Modes in AI-Supported Learning

Phase Components	Phase 1: Analytics Framework Development	Phase 2: Data Collection and Primary Analysis	Phase 3: Integration and Pattern Analysis
Primary Focus	Development of classification framework and validation	Data collection and initial analysis	Comprehensive analysis and model development
Key Activities	ICAP classification scheme creation, NLP algorithm development, Classification rule establishment	Collection of interaction logs, Implementation of classification, Sequential pattern mining	Pattern analysis across modes, Relationship investigation, Temporal analysis
Validation Steps	Expert review, Pilot testing, Algorithm refinement	Manual validation, Classification refinement, Initial correlation analysis	Expert pattern review, Cross-cohort validation, Model validation
Outputs	Validated classification framework, Quality metrics, Reliability measures	Classified engagement patterns, Initial relationships, Preliminary models	Predictive models, Engagement guidelines, Intervention frameworks

In summary, the study will address the three primary research questions through specific analytical approaches: RQ1 examines how nursing students' interactions with SPAI align with ICAP modes through NLP analysis of chat dialogues, pattern recognition in interaction sequences, and automated classification of engagement modes. Data sources will include chat transcripts, system logs, and session metrics, producing outputs of ICAP mode distribution and engagement patterns. RQ2 investigates relationships between engagement patterns and learning outcomes through correlation analysis and predictive modeling. This includes examining engagement patterns versus course performance, mode transitions versus learning progression, and developing regression models of engagement factors. Data sources combine ICAP classification results with course performance metrics. RQ3 explores how to support effective AI-learning interactions through pattern analysis and qualitative examination. Methods include identifying successful engagement sequences, comparing high versus low performing students, and analyzing dialogue quality. This analysis draws from classified ICAP patterns, performance data, and dialogue metrics.

5. Expected Outcomes, Potential Limitations and Impact

Primary outcomes of this study focus on ICAP mode distribution (frequency, progression patterns, duration, transitions) and learning performance (course examinations such as HESI Specialty Exams). Secondary outcomes examine engagement quality metrics including dialogue depth, content quality, and self-regulation indicators. These outcomes will contribute to several broader areas of impact in nursing education and AI-supported learning.

First, understanding the relationship between engagement patterns and learning outcomes will inform the design of more effective AI-supported learning environments in nursing education. Second, the methodological framework developed through this study will provide a structured approach for analyzing student-AI interactions in healthcare education more broadly. Finally, insights from this research will contribute to our understanding of how to effectively integrate AI tools into nursing education in ways that support both knowledge acquisition and the development of critical thinking skills. This understanding is particularly crucial as nursing education continues to evolve with technological advancement, requiring evidence-based approaches to technology integration that maintain pedagogical effectiveness.

Several important limitations and potential sources of bias must be acknowledged in this study. First, the analysis of student engagement through digital trace data may not capture the full complexity of learning interactions. While the ICAP framework provides a structured approach for classifying observable behaviors, students' internal cognitive processes and motivations may not be fully reflected in their digital interactions. Technical limitations include the constraints of NLP in accurately classifying engagement modes, particularly for complex or ambiguous interactions. The automated classification system may require ongoing refinement and validation to ensure reliable categorization of student engagement patterns.

Potential biases include: (a) Selection bias: Students' comfort level with technology may influence their engagement patterns; (b) Measurement bias: The focus on quantifiable interactions may undervalue qualitative aspects of learning; and (c) Temporal bias: Student engagement patterns may vary across the academic term. Additionally, the study's focus on a single AI system (Sherpath AI) within one educational context may limit generalizability. While findings may inform understanding of AI-supported learning broadly, specific patterns may not transfer directly to other educational contexts or AI platforms. To address these limitations, the study incorporates multiple validation approaches and acknowledges these constraints in interpreting results and forming recommendations.

This research can advance both learning analytics and nursing education in several critical ways. For learning analytics, it can demonstrate how educational theory (ICAP) can be systematically integrated into analytics frameworks, addressing a persistent gap in the field [10]. This integration provides a model for theory-driven learning analytics that could be adapted for other educational contexts. For nursing education, this work can establish a foundation for evidence-based approaches for understanding and optimizing AI-supported learning, particularly crucial as nursing programs are increasingly adopting AI tools. The methodological framework developed through this research can provide nursing educators with concrete tools for evaluating and enhancing student engagement with AI learning companions such as Sherpath AI.

Declaration on Generative AI

Generative AI tools have not been used by the author to prepare the submission.

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