Proposal

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Abstract—Since the advent of ChatGPT in 2023, the educational landscape has undergone a significant metamorphosis. While Large Language Models (LLMs) offer unparalleled capabilities in information extraction and human-esque communication, concerns arise regarding their impact on students' cognitive engagement. This study introduces the Interactive-Constructive-Active Learning Machine (ICALM), an avant-garde Intelligent Tutoring System that synergizes with the ICAP Framework Chi and Wylie, 2014. ICALM integrates a triad of functionalities: concept map generation from flashcards, a knowledge-graph based recommendation system promoting exploration, and LLM-facilitated active learning that encompasses chatbot interactions and reflective essays. Central to this system is the progression from mere content absorption to heightened engagement levels—transitioning from content reading to paraphrasing, concept mapping, and peer discussions. Leveraging AI, ICALM ensures a structured comprehension of course materials and promotes a shift in concept mapping from a constructive endeavor to an active learning experience. The system culminates in an interactive learning task, drawing inspiration from the Inclass portfolio Walvoord, Stevens, and Levi, 2013, and incorporates calibrated feedback mechanisms powered by LLMs.

1 INTRODUCTION

Since the inception of ChatGPT in early 2023, there has been a notable transformation in the educational sector. Large Language Models (LLMs) have exhibited remarkable capabilities in information retrieval and the composition of human-like responses. This development has led to concerns, as students can now effortlessly obtain answers from educators' meticulously crafted questions, bypassing their own cognitive engagement with the material. Nevertheless, these challenges also pave the way for potential advancements. Techniques to engage students in online learning can be more effectively integrated into their pre-class, in-class, and post-class activities, particularly for tasks demanding constructive and self-motivated study.

The importance of academic preparedness for post-secondary education cannot be understated, as evidenced by the research of Dolores Perin, Professor Emerita of Psychology and Education at Columbia University, in her recent work, Academic Preparedness, laid out four factors are contributing to concerns for academic preparedness in the United States (Flippo and Bean, 2018). Those are improved importance of college degree (Kroeger, Cooke, and Gould, 2016), low college completion rate of 59.4% and lower community college completion rate of 27.9% (Snyder, Brey, and Dillow, 2016) , difficulty in reading demonstrated by majority (62%) of US 12th graders (Education Statistics, Education Sciences, 2012, 2014), and ineffective college support programs (Xu, 2017). The low literacy skills are especially risky as the it is associated with the ability to interpret, comprehend and apply knowledge in textual form (Flippo and Bean, 2018). Furthermore, a study on reading requirements has shown that the general expectation of the instructors at a community college is for students to read and comprehend key concepts the assigned readings independently before class. However, the students are found having difficulties in understanding the texts which lead to extensive lecture time on explaining the concepts (Armstrong, Stahl, Kantner, 2015a, 2015b, 2016).

Due to the textbooks of the most introductory general education courses at colleges are written at the 12th-grade readability level or higher, the students in grade 12, taking Advancement Placement exams and in entry-level post secondary courses are few of the most crucial group to be supported with their learning skills to improve their academic preparedness. Students in the above groups confront a stark of increase in the volume and complexity of information they must internalize, requiring them to shift from rote memorization to a more holistic, structured understanding with building connections between diverse concepts. Also, as outlined by Jean Piaget's theory of cognitive development, students between the age of 15 and 22 are transitioning from the concrete operational stage to formal operational thought, during which adolescents and young adults begin to think more abstractly, reason about hypothetical concepts (Piaget, 1964). Hence, a tool that breaking down the rigorous topics, forming structures and making them more digestible has been called for.

Concept mapping is a widely-recognized strategy that enables students to visually represent information, helping in organizing and understanding complex ideas

(Hay, 2007). The current research landscape emphasizes technological applications for creating these maps, as well as their integration into online learning platforms (Cheung, Perry and Winne, Hwang, Yang, and Wang, 2006, 2006, 2013). Specifically, Perry and Winne's gStudy software incorporates concept mapping to bolster self-regulated learning. The versatility of maps ranges from illustrating hierarchical structures to highlighting intricate interconnections between ideas. Such mappings not only foster links between concepts but also enhance students' metacognitive understanding of the content (Nesbit and Adesope, 2006). They act as facilitators across diverse subjects, allowing students to structure information, correlate it with their existing knowledge, and provide personalized examples (Lipson, 1995).

Concept mapping offers several benefits, notably spotlighting connections among ideas and aiding deeper information processing (Lipson, 1995). Furthermore, it's an effective strategy for information retrieval (Blunt and Karpicke, 2014). This learning strategy's effectiveness demands students to have developed metacognitive capabilities to discern interrelationships among ideas. Some research highlights potential reservations among students with limited content knowledge regarding concept mapping (Hadwin and Winne, 1996). To maximize the potential of graphic organizers, educators must provide direct guidance, opportunities for practice, and feedback for students progressively, as the information becomes extensive and the organizational patterns become more complex (Flippo and Bean, 2018).

In the future study, we present the design of the Interactive-Constructive-Active Learning Machine (ICALM), an advanced Intelligent Tutoring System. The ICALM comprises three main components: a) Entity-relation (ER) extractions, which generate concept maps from flashcards; b) a knowledge-graph based recommendation system facilitating student exposure to the most pertinent, intriguing, or peer-favored topics, thus fostering discussion and exploration; c) an active learning component where students utilize LLM-based chatbots to verify information and defend their perspectives; d) concluding with a reflective essay session where students contemplate their learnings, which is then juxtaposed with a summary generated by LLMs.

The structured learning stages align with the ICAP Framework, an instructional approach introduced by Chi and Wylie, 2014. The framework categorizes overt learning behaviors into Passive, Active, Constructive, and Interactive, arranged from least to most effective. Rather than employing cognition terms from Bloom's taxonomy, this approach assesses student outcomes based on their adherence to task instructions specific to each category. To elaborate, student engagement levels should ideally escalate from mere content reading to paraphrasing, concept mapping, and peer discussions, respectively.

Similar to the original ICAP Framework, The system we delineate adheres to a conceptualized four-stage knowledge-processing sequence: storage, integration, inference, and collaborative inference Chi and Wylie, 2014. The emphasis is on reorganizing the structural integrity of course materials, enabling logical comprehension rather than mere replication of original or paraphrased content. The AI-assisted concept mapping in component b) optimizes the initial content consumption phase, leading to an active engagement with logically structured and hierarchically presented information. Notably, within this system, concept mapping transitions from a constructive task to an active learning one. This shift simplifies the initiation of the learning process, enhancing student engagement. Processes in component c) utilize specifically tailored ChatGPT templates, enabling students to build upon their existing knowledge base. For instance, within an Economics module, students might explore "historical events linked to rising interest rates", subsequently attempting to elucidate "the repercussions of increased interest rates" utilizing foundational course materials. The former represents system-facilitated constructive learning, while the latter exemplifies interactive learning. Component d) draws from the SET 45 - In-class portfolio, as outlined in the *"Student Engagement Techniques - A Handbook for College Faculty"* Barkley, 2009, with LLMs providing calibrated feedback and scaffolding, culminating the session with an interactive learning task.

In response to the mentioned academic challenges, advanced Intelligent Tutoring Systems, such as ICALM, are at the forefront of potential solutions. The ICALM system integrates the principles of the ICAP Framework, emphasizing a progression from passive to active and ultimately, to interactive learning behaviors. Its sophisticated design not only aids in the storage and integration of knowledge but fosters inference-making and collaborative interactions. With its multi-faceted components, ICALM offers students a comprehensive learning experience, moving beyond traditional educational methods and leveraging the capabilities of LLMs. Such innovative approaches can play a pivotal role in addressing academic preparedness concerns and sculpting a more adaptive and inclusive learning landscape.

2 RELATED WORK

2.1 The ICAP Framework

Originating from a study by Chi and Wylie, the ICAP framework delineates a taxonomy that encompasses four distinct modes of cognitive engagement, namely Interactive, Constructive, Active, and Passive. While Bloom's taxonomy Athanassiou, McNett, and Harvey, 2003 primarily concentrates on instructional objectives, ICAP pivots on overt behaviors of students to gauge achievement. By empirically examining three engagement paradigms - note-taking, concept mapping, and self-examination - the authors deduced a hierarchy of efficacy from Interactive to Passive modes. This framework delineates the nuances among active, constructive, and interactive learnings, providing specific definitions for each.

2.2 Human Cognition

The capacity of working memory, instrumental in the transient storage and manipulation of information, is believed to be constrained to 3-5 chunks of information Cowan, 2010. Nevertheless, strategies such as chunking enable individuals to optimize their memory utilization. Although the underpinnings of this constraint remain contentious, some ascribe it to biological limitations. As learning involves the interplay between short-term and long-term memory, innovations like Limbiks, Revisely, and Gizmo AI aim to convert information into digestible formats to enhance learning efficiency.

2.3 Knowledge Graph

Knowledge graphs epitomize heterogeneous networks, representing entities and their relationships through nodes and edges. This computationally-intensive architecture has prompted exploration into attention networks integrated within Graph Neural Networks (GNN). While models like GAT Veličković et al., 2018 have shown promise, the nuanced efficacy of attention mechanisms in GNN demands intricate design considerations, as evidenced by models like GC-SAN Xu et al., 2019 and SR-GNN Wu et al., 2019.

2.4 Named Entity Relation Extractor

Constructing a knowledge graph necessitates the upstream extraction of semantic relationships from raw datasets, often formatted as triplets. Recent developments, such as REBEL by Huguet Cabot and Navigli, have leveraged BERT-based Seq2Seq models to treat entity-relation extraction and classification tasks as analogous to translation tasks. Further innovations, such as KnowGL by Rossiello et al., have expanded upon this approach, enhancing the granularity and richness of entity labels and relationships.

2.5 Recommender System

Session-based recommendation systems, historically grounded in methods like collaborative filtering, predict user behaviors based on historical interactions. However, as the scale of users and items has burgeoned, matrix representations have become increasingly unwieldy. Despite the initial promise of Recurrent Neural Networks (RNN) in this domain, their efficacy is hampered by data limitations and lack of context. Hence, emerging methodologies, including those encapsulated in SR-GNN Wu et al., 2019, strive to capitalize on the rich contextual data inherent in user behaviors. Parallelly, there is a burgeoning demand for greater transparency and explainability in recommender systems, underscored by the complexities of specific application domains.

2.6 Knowledge Graph Based Recommender System

To redress the aforementioned shortcomings, recommender systems underpinned by knowledge graphs have gained traction. Their inherent ability to discern latent connections and provide holistic, semantically-rich recommendations has rendered them particularly appealing. While various methodologies exist within this paradigm, such as path-based embeddings and unified methods, the most apt approach is contingent on the specific application context. While these systems offer considerable advantages, they also introduce computational challenges. Consequently, knowledge graph embedding methods have been devised to reduce the dimensionality of representations. However, these come with trade-offs, especially in terms of explainability. Recent innovations, such as HAGERec Yang and Dong, 2020 and KGAT Wang et al., 2019b, while reducing the need for manual meta-graph optimization, grapple with challenges like cold start issues and computational overheads.

3 PROPOSED FRAMEWORK

3.1 Overview

This section is dedicated on the design of the ICALM Intelligent Tutoring System, which is designed to integrate entity extraction, knowledge graph construction, and constructive reflection writing. The knowledge graphs, termed concept maps herein, are explicitly presented to users. The system's functionality encompasses recommending subsequent topics based on the congruity with the present topic, user predilections, and/or the inclinations of other learners. Upon solicitation, the system offers a comprehensive exposition on a selected topic. Conclusively, after each instructional session, learners are prompted to compose a brief reflection essay, approximating a one-minute duration, to introspect on acquired knowledge. This reflection will be subsequently juxtaposed with results generated by an LLM model.

3.2 Automated Knowledge Graph Constructor

ICALM's core function is to transform flashcards into knowledge graphs and proffer recommendations for subsequent topics, contingent upon a user's content consumption history and the transitional dynamics observed within academic concepts.

Initially, this system harnesses the capabilities of KnowGL from IBM Research AI consortium Rossiello et al., 2022. This model is adept at extracting salient facts from textual sources, subsequently converting them to linearized semantic representation triplets that encompass subject, relation label, and object. Contrasting with the preliminary endeavors of Babel, this representation is exhaustive, embracing both ABox assertions and TBox meta-information regarding entity labels and classifications. During its training phase, KnowGL augments the foundational REBEL dataset (Huguet Cabot and Navigli, 2021) with ancillary entity labels, types, and their morphological forms. The model's principal objective revolves around optimizing the mapping outcomes through cross-entropy loss, concurrently maximizing the log-likelihood of fact generation.

The resulting triplets from KnowGL serve as the foundation for constructing knowledge graphs. These are further utilized by a recommender system to curate subsequent topic suggestions. This system incorporates RippleNet (Wang et al., 2018), an amalgam of embedding-based and path-based methodologies, to execute an end-to-end recommendation process. The RippleNet system, cognizant of knowledge-graph structures, initiates user preference propagation over a knowledge graph, and in iterative cycles, offers recommendations rooted in a user's antecedent selections. As a consequence, this model facilitates topic recommendations not merely based on relational chains but also varied elements situated on the peripheral ripples.

Subsequent tables showcase a comparative analysis between RippleNet (Wang et al., 2018), CKE Zhang et al., 2016, KGCN (Wang et al., 2019a), etc., focusing on metrics like AUC and temporal efficiency, sourced from RecBole's implementations Zhao et al., 2022

	AUC	Time(s)
RippleNet (Wang et al., 2018)	0.899	~360
CKE (Zhang et al., 2016)	0.903	28.76
KGCN (Wang et al., 2019a)	0.921	48.75
CFKG (Ai et al., 2018)	0.921	31.58
KTUP (Cao et al., 2019)	0.864	47.59

Table 1—AUC of (Knowledge) Graph Based Recommendations

3.3 LLM-Based Task Generation

Given the prowess of Large Language Models (LLMs) in conventional Natural Language Processing paradigms, their bespoke fine-tuning for specialized tasks remains a formidable challenge. Therefore, this research endeavor involves refining the GPT model using pedagogical materials resembling textbooks. The refined model is then prompted to compose in-class portfolios that align with predetermined assessment criteria. The results, algorithmically generated, undergo offline scrutiny using tools like SocialIQA (for Arts) and PhysicalIQA (for STEM subjects) (Sap et al., 2019) and online juxtaposition with student inputs via Sentence-BERT (Reimers and Gurevych, 2019). This tool facilitates the generation of encodings for both inputs, enabling the computation of cosine similarity. Feedback mechanisms are also integrated, emphasizing the nuances of note quality, lucidity, and comprehensive coverage of curriculum content.

3.4 Research Questions

In the realm of educational technology (EdTech), contemporary research explores the integration of Large Language Models (LLMs) and Knowledge Graphs (KGs) to optimize student engagement and learning outcomes. The potential optimizations in these methods give rise to essential research questions in the context of prevailing educational challenges:

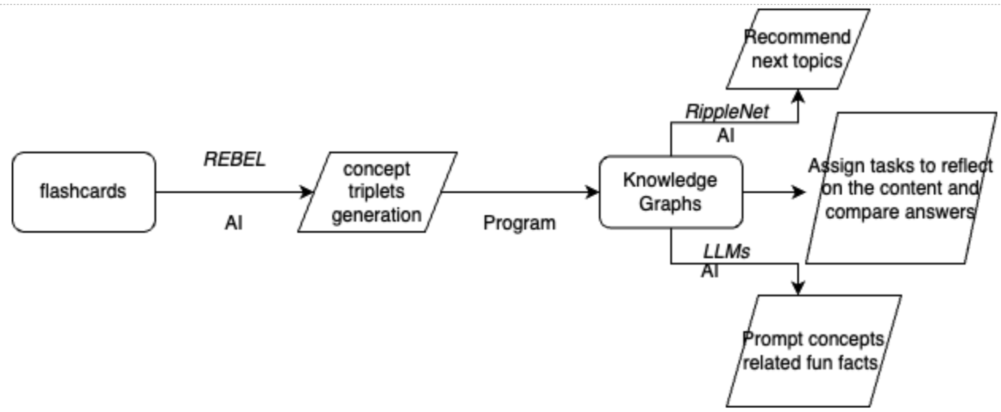

Figure 1—Workflow of ICALM Framework

3.4.1 *How do explicit representations of Knowledge Graphs influence student comprehension compared to simple turn-wise conversations with LLMs?*

This question emerges from a need to discern the comparative efficacy of explicit Knowledge Graphs (KGs) and turn-wise interactions with Large Language Models (LLMs). It offers a focused examination into the nuanced mechanisms by which KGs and LLMs potentially influence comprehension, echoing recent findings by Petroni et al. (2019) that LLMs share capabilities with KGs. The question is structured to dig deeper, analyzing the multilayered reconstruction of knowledge through KGs versus the transcriptive knowledge of conversational chatbots. It remains a topic of debate how these mechanisms fare in educational settings, hence this inquiry.

In order to implement a mixed-method approach, where quantitative data is collected through pre- and post-tests to measure comprehension levels after students interact with either KGs or LLMs. Follow this with qualitative feedback through structured interviews, gaining insights into their preferences and perceived challenges with each method.

3.4.2 *Given the shortening attention spans (Mark, 2023), how can EdTech platforms, leveraging LLMs and KGs, offer bite-sized and graph-structured materials that juxtaposes with standardized test frameworks?*

Addressing the prevalent challenge of dwindling attention spans among students, this question zeroes in on the design strategies of EdTech platforms. With an emphasis on aligning with standardized tests and Ministry of Education directives, it ponders how EdTech can optimize content delivery using KGs and LLMs while being sensitive to students' cognitive bandwidth.

We would conduct an A/B testing following the design outlined from *A/B Testing: The Most Powerful Way to Turn Clicks Into Customers* by Siroker and Koomen with each pair of the treatments as one condition.

(a) Knowledge graph-based representation with recommendations for related concepts.
(b) LLM-based quizzing and search tools to assist during the learning session.
(c) LLM-driven reflection at the end of the learning session to reinforce knowledge absorption.
(d) Control group where no specific treatment is applied.

The table showcases the combinations of these components.

Group	Treatment Combination
A	a: Knowledge graph only
B	b: LLM-based quizzing only
C	c: LLM-driven reflections only
D	d: Control (no treatments)
E	$a + b$: Knowledge graph + quizzing
F	$a + c$: Knowledge graph + reflection
G	$b + c$: Quizzing + reflection
H	$a + b + c$: All treatments

Table 2—Contingency Table of Student Learning Group Treatments

The study will recruit high school seniors and college freshmen preparing for standardized tests, ensuring a diverse and relevant participant pool. Students will be randomly assigned to one of eight groups based on the contingency table, with treatments designed to compare the effects of knowledge graph-based learning, LLM-based quizzing, LLM-driven reflection, and their combinations. Sample sizes will be determined using power analysis to ensure statistically significant results.

The treatments will focus on distinct learning interventions:

(a) Knowledge Graphs (Treatment a): Students will explore content through hierarchical, graph-based representations, highlighting connections between topics.
(b) LLM Quizzing and Search Tools (Treatment b): Interactive quizzes and search tools will reinforce active learning.
(c) LLM-Driven Reflection (Treatment c): Post-session reflective writing exercises will help students consolidate their understanding, with LLM-generated summaries providing comparison.
(d) Control Group (Treatment d): Students will use traditional learning materials without any intervention. The groups combining these treatments will explore the synergistic effects of multiple strategies.

The study will consist of a pre-test to establish baseline knowledge, followed by a four-week learning period where participants engage with their assigned treatments. Sessions will be held online or in controlled classroom environments. A post-test will assess improvements in comprehension and retention using the same standardized test as the pre-test.

Quantitative data will include pre- and post-test scores to measure knowledge gains and engagement metrics like time spent on tasks and interaction rates. Qualitative data will be gathered through post-study surveys and analysis of reflective essays, providing insights into participants' perceptions of ease, engagement, and satisfaction.

The study will use statistical methods such as ANOVA to compare test score improvements across groups. Correlations between engagement metrics and performance will be analyzed, while qualitative responses will undergo thematic analysis to identify trends in user experiences.

Students receiving interventions are expected to show greater improvements in test scores than the control group, with combined interventions yielding the highest gains. The group receiving all treatments is hypothesized to exhibit the highest engagement and retention levels.

A pilot study will precede the full experiment to refine materials, validate instructions, and address any logistical challenges.

3.4.3 *How can student-centered techniques, like structured reflections and peer connections, be effectively incorporated into EdTech platforms powered by LLMs and/or KGs?*

Barkley highlight an array of student engagement techniques, with particular emphasis on structured reflections and peer connections (Barkley, 2020). Given their well-documented efficacy, it becomes paramount to explore their integration into EdTech platforms, particularly those utilizing KGs and LLMs. This question contemplates practical methods of blending these pedagogical strategies with cutting-edge technological tools.

In order to answer this question, we will deploy prototype EdTech platforms as a web platform with and without the student-centered techniques and track student engagement metrics over a semester. At the end of the term, distribute questionnaires assessing students' satisfaction, perceived learning outcomes, and any suggestions for platform improvement.

4 DELIVERABLES

Two intermediate milestones and a final project will be delivered:

- **First Milestone:** Initial design and prototype of ICALM, incorporating entity extraction and knowledge graph construction.
- **Second Milestone:** Integration of the LLM-based task generation and preliminary testing with select student groups.
- **Final Milestone:** The complete ICALM tool, including all functionalities, user documentation, and results from pilot testing.

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