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Envisioning AI-powered Learning Stemming from Piloted Personalized Education

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Abstract

Learning systems can potentially transform education and training by allowing educators to encourage behavioural changes and internalization of concepts in learners. This paper introduces such an AI-powered model for a personalized learning system, building on our success of hand-curated learning paths to support individualized education.

We utilize a network science approach as a construct to create an environment that is supportive of an individualized learning process, presenting an AI-powered framework. This framework is informed by student and faculty interactions with two custom created learning systems, experiences that shaped goals and expectations of the proposed AI-powered method since 2018.

This paper contributes to advancing the conversation around AI-powered learning systems and personalizing educational experiences. Our AI-powered model engages learners in their educational journey through individualized and adaptive learning paths, while meeting each learners' specific learning outcomes. We conclude with open research problems that surfaced from this vision.

Keywords: *Innovating teaching and learning experiences; AI-powered learning; personalized learning; individualized learning; AI-infused education model.*

1. Introduction

Traditional forms of education involve uniform instruction presented at the same pace and schedule for all learners. This approach may result in a lack of effective student engagement and often includes some learners being over and under challenged. Moreover, these educational models have the high potential to produce graduates with similar skill levels, rather than providing a platform for enhancing learners' existing skills and talents. Recent methods have explored the use of AI in classrooms through hands on projects to improve the learning environment, yet at scale success is still needed (Kumar et al., 2006, Zhang & Aslan, 2021).

A responsive way of engaging learners with educational content would be to map out personalized and adaptable learning modules, catering to each learner's existing knowledge levels and specific interests. In this environment, learning is driven by individualized learning outcomes by filling in the identified gaps. This facilitates the cultivation of a learning culture where individuals, while balancing personal and professional responsibilities, can engage in lifelong learning that complements formal education (Gera et al., 2019, Raj & Renumol, 2022, Reinhardt & Elwood, 2019).

In this paper, we introduce an AI-powered model for a Learning and Development System (LDS) that uses a non-traditional educational approach guiding students through a repository of networked micro-learning modules supporting personalized learning. LDS's micro-learning modules facilitate targeted and adaptive learning opportunities, to complement students' knowledge, skills, and abilities when ideally suited. We envision a world where personalized AI-powered learning technologies build upon students' unique knowledge backgrounds while challenging them to realize their full potential. Our AI-powered learning model for personalized learning is an approach that differs significantly from the traditional ones, aiming to improve students' focused engagement, support their unique circumstances, and lead to meeting tailored learning outcomes.

2. The Model: Creating the AI-powered Personalized Learning Experience

To ensure an effective personalized learning experience, it is imperative to capture relevant learner information automatically. This can be achieved by creating a dynamic learner profile that collects the necessary information stored as tags, such as the learner's employment, existing education, interests, personality, preferences, and accessibility of resources. Additionally, this information can be dynamically updated based on assessments and individualized learning experiences, allowing for continually personalized learning. This data is then used to personalize the experience and motivate the learner through a combination of intrinsic and extrinsic factors. Some examples of learner profile components could be learner's goals (such as "learner needs basic concepts of AI"), learning outcomes (such as "learner wants to use AI to help improve writing skills"), inferred competencies (such as "learner validated Unsupervised Learning as he previously used clustering and association rules in data analysis"), environment constraints (such as the "learner rides the bus for 30 min daily during the light study session and is available only 1 hour a week for deeper sessions") and so on.

2.1. The Learning Environment

Based on each learner's assessment and learning outcomes, content from a repository could be pulled to create a path, a sequence of individualized content, for each learner individually, where the personalization is guided by the learner profile content. We proposed to overlay a network of knowledge framework over a semi-structured learning material repository to guide learning path creation. Figure 1 introduces a visual of the correspondence between the information saved in the learner profile on the left, and the learning paths highlighted in yellow through a network of knowledge on the right. This style of creating learning paths has been successfully used by the authors since 2018 in graduate level courses (citations added once authors are added, post double-blind review).

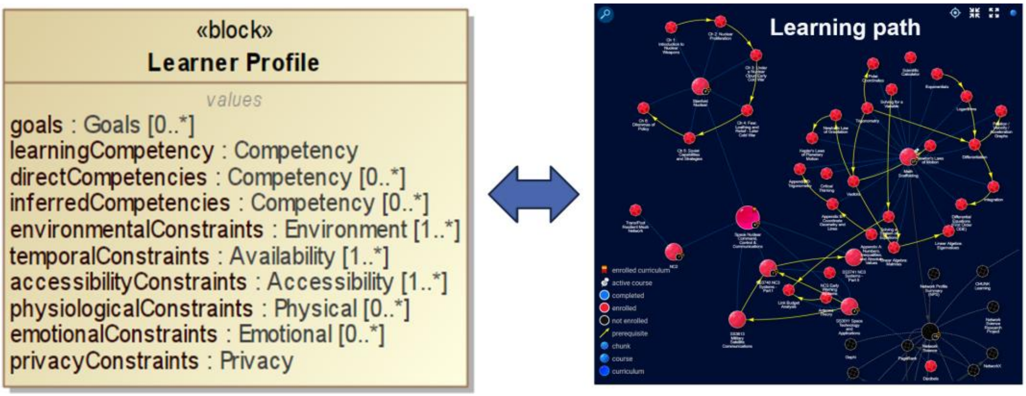

Figure 1: Individual learner profile information influence learning paths, while dynamically updating based on the individual learner's progress of the learning path

While this strategy of creating learning paths was a successful model, it did not scale as the authors had to find content, tag it appropriately, connect in the network, and create each individualized learning path based on each learner's profile. We propose a scalable model for personalized learning based on the functionality of AI that can overcome the limitations of relying heavily on human intervention.

We thus propose the idea of an automated approach of curating data and creating a personalized learning path for each individual, ensuring relevant and engaging content while supporting the curator as well. The real-time, continuous adaptation of learning paths makes education engaging, enhancing the quality and diversity of learning experiences. The implications of this model on educational practices could be significant, advancing our practices of personalized learning in the digital age.

Our four-step methodology for the AI-powered personalized education model is illustrated in Figure 2. Based on the above-mentioned non-AI model that we have piloted, our proposed approach utilizes a networked environment of micro-learning materials to create AI-powered tailored educational experience as we describe next.

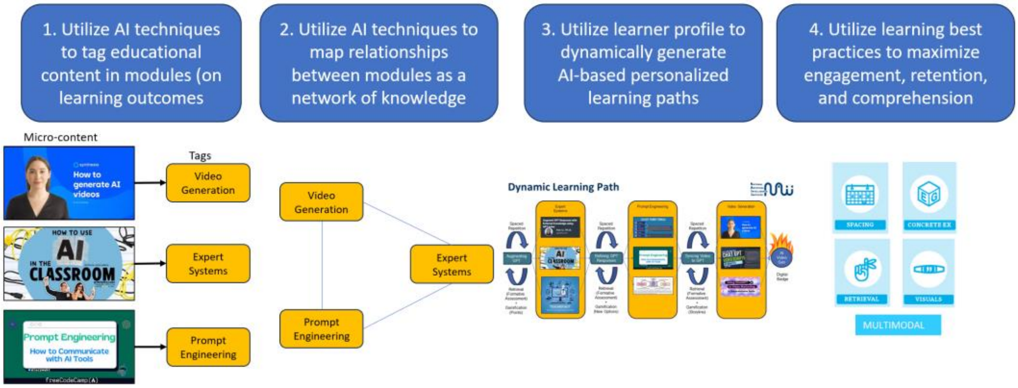

Figure 2: Our 4-step AI-powered model of tagging content, creating a networked framework, and identifying tailored learning paths through the network of knowledge to personalize the learning for each student based on each learner's profile (for readability Step 3 is enlarged in Figure 3)

The first step is AI-powered tagging of flexible micro-modules to support the creation of a tagged-rich environment. Our approach assumes that an abundance of content is available for a given topic to be learned. This data could be tagged (categorized) through multiple strategies including pattern recognition, machine learning, or term frequency/structure analysis. Tagging is important because AI is imperfect and human intervention may be necessary. Proper micro-module tagging is vital for a well-organized learning environment, and AI can help achieve this effectively. Moreover, based on the tags, AI can assist in addressing content gaps required for effective new content creation.

In the second step of our methodology depicted in Figure 2, we introduce the concept of creating a framework that automatically produces a network of knowledge as a collection of educational modules to support 21st-century learners. This network of knowledge is constructed by inspecting the structure and relationships between terms within content and existing courses. For example, the table of contents from a textbook or syllabus, or the keywords that a video is tagged with, provide the universe of related generalizations that are then linked by the content within the chapters and curriculum. The advantage of visualizing these relationships within a graph involves the ability of a human instructor to make adjustments. This is similar to prior work as illustrated in Figure 1 as yellow learning paths. Unlike a traditional textbook whose content is strategically sequenced and static once published, our micro-lectures repository of knowledge is dynamic in time as authors add added content or older content becomes obsolete. Thus, we propose that a model is needed to curate a network of knowledge that incorporates network evolution to support dynamic growth and retirement of micro-content (such as PDFs, videos, code, PPT, simulations, examples, exercises, etc.). This network's function is to allow the creation of personalized and adaptive learning paths to enhance learner's education by filling in the exact missing gaps while building on each learner's knowledge and experiences.

In the third step of our methodology depicted in Figure 2, we create dynamic personalized learning paths. Much like a GPS dynamically adjusts a driving path from a source to a destination while roads are being built or closed, the structure of the network of knowledge's content allows a recommender system to assist the learner in moving through the educational materials even while the network evolves. Based on each learner's background, the system would provide different choices in how to engage the learning content, while ensuring the learner reached the desired destination meeting the individualized learning goals. Each student benefits differently from the available content as the suggested learning materials also build on learners' pre-existing knowledge.

Lastly, in the fourth step of our methodology depicted in Figure 2, we augment the recommendation of the learning paths based on best learning science practices, such as using multimodal content to engage multiple senses, space-repetition, relevant to each user application, and so on (Anderson, 2016, Jarvis, 2004, Kang, 2016, Kress et al. 2006, Merriam & Bierema, 2013, Seibert Hanson & Brown, 2020). This is accomplished in a variety of ways. Spaced repetition will likely be determined by parameters determined from past learning engagements. Similarly, gamification techniques could be determined by how well prior techniques were received by the learner. Additionally, we adjust the content and the interaction with the content based on learner feedback by updated parameters within the learner's profile.

2.2. An Example of Personalizing the AI-powered Learning Paths

Our AI-powered personalized education model creates learner-focused learning paths using interchangeable micro-learning content from the network of knowledge. The AI-identified content tags help in organizing the content into coherent and cross-referenced learning paths towards meeting the chosen learning outcomes. Figure 3 depicts this process by showing a portion of a learning path as the learner engages with "Expert Systems" content, followed by "Prompt Engineering" and later by "Video Generation" content.

We emphasize that the model should be content agnostic, we rather use particular topics as an example. Also, the content is multimodal for each of the three topics of this example, to support multiple sensory engagement. That is, the learners can engage with several types of content, such as videos, podcasts, images, PDF, and interactive activities to capture learners' interests and provide a more engaging experience. Additionally, we sprinkle space repetition between contents to solidify learning and facilitate retention.

The tags created by AI help identify what content can be swapped for what other content to meet the multimodal experience. This recommendation is achieved based on the learner's profile information, content preference, and performance on formative assessments and other learning activities. To optimize the learning journey, we use gamification elements to support motivation and engagement supporting lifelong learners. This highly personalized approach makes learning adaptive, responsive, effective, and engaging for learners of all levels and backgrounds (Anastopoulou et al., 2003, Jewitt, 2008).

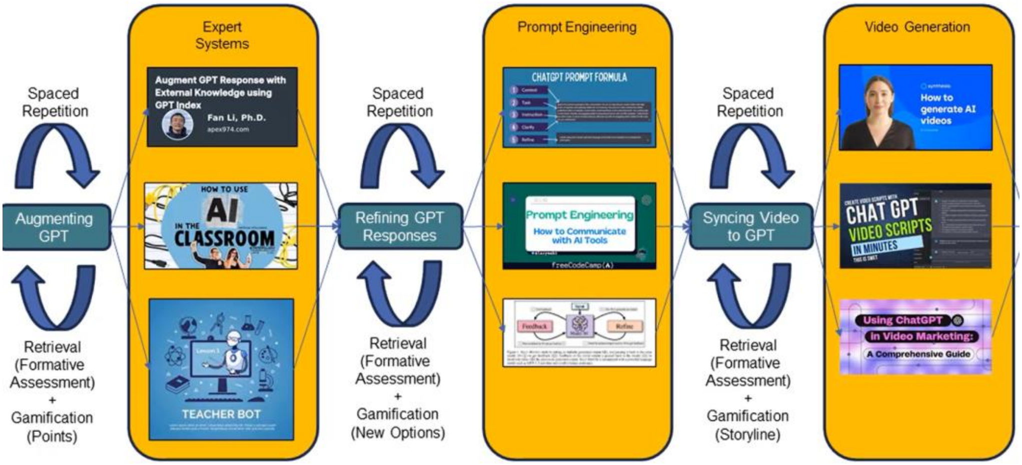

Figure 3. An AI-powered dynamic learning path

Overall, our methodology enables a scalable AI-supported personalized learning environment. By leveraging content tagging, networked content, multimodal presentation, and AI-assisted learning path creation, learners can benefit from a tailored educational experience that enhances engagement, knowledge retention, and performance.

3. Future Work and Conclusions

Learning methods that promise novel approaches to education and training still face the challenges of transitioning from merely sharing information to educating and developing learners. Generally, learning platforms tend to reflect an evolution of the physical classroom into a virtual experience. In this work, we present an alternative to that learning process by creating AI-powered learning paths based on a previously used novel learning model that utilized hand tagged content, networked content, and curated learning paths.

Our work addresses these challenges by proposing an AI-powered learning framework that leverages AI technology to meet the educational outcomes and provide flexibility by personalizing journey of the learner. We propose that a learning and developing system that personalizes the learning experience is needed to present learning content by scaffolding knowledge based on 1) the learner's goals, constraints, and behavior, 2) knowledge structure of materials, and 3) assessment mechanisms and achievement records. Our proposed AI-powered framework consists of a four-step novel construct to automatize each aspect of the individualized learning journey and to advance personalized educational experiences represented by learning paths.

Our theoretical framework is informed by student and faculty interactions with two operational learning platforms. We built these learning platforms and they have now endured the scrutiny of students and faculty since 2018, whose feedback has shaped our goals and expectations for this work. Our framework creates an individualized learning experience supported by micro-learning content, building on assessments guided by learning outcomes. While these ideas can create a personalized environment, research is needed in identifying how to meet this vision. We thus conclude with open research questions to take this work towards implementation:

1. What is a good framework for a dynamic network of knowledge to incorporate network's evolution, as the curated repository of micro-learning allows updated content to be added, existing content to be updated, and old non-relevant content to be retired? This structure needs to ensure content discoverability by learners and curators, otherwise we end up with gaps as content retires, or we end up with content that nobody is presented as alternatives.
2. How can AI assist in addressing content gaps required for effective content creation to fill in the gaps that learning paths might have?
3. How can automatically personalized and adaptable learning paths be created, addressing tailored gaps in knowledge, while providing a cohesive learning experience for each user (as each learning path is generated while the learner progresses)?

Adult learning theory supports that learning takes place best when learners are actively engaged with relevant content, in a self-directed modality (heutagogy), through multimodal methods, uses space-repetition, and supported by peers. Relevant content is critical to adult learners' motivation and engagement, as learners should have opportunities to make content connections with their subjective experiences and skills development that support their professional education. Therefore, adult learners need an attention-grabbing, contextualized, interactive, and collaborative environment that facilitates their learning and meets their specific learning needs. We addressed the first four components in this research, and we further recommend that social learning be considered in future research, to have a comprehensive learning and development system. Future work also includes implementation and quantitative measures.

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