# Chapter # 27

# PERSONALIZING LEARNING THROUGH COLLABORATIVE NETWORKS OF KNOWLEDGE

**Ralucca Gera[1], Mark Reith[2], D'Marie Bartolf[3], Simona Tick[4], Paolo Singh[1], Sean Mochocki[2], & Akrati Saxena[5]**
[1]*Department of Applied Mathematics, Naval Postgraduate School, USA*
[2]*Graduate School of Engineering and Management, Air Force Institute of Technology, USA*
[3]*QuantHub, USA*
[4]*Department of Defense Management, Naval Postgraduate School, USA*
[5]*Leiden Institute of Advanced Computer Science, Leiden University, The Netherlands*

**ABSTRACT**
Over the past two decades, numerous learning systems have emerged promising novel approaches to improve education and training. However, most rely on exposure to information and practice, which does not guarantee the internalization of the concepts and changes in behavior required to engage the learner appropriately in education and training. This paper presents a new learning process that addresses these limitations by modeling, motivating, guiding, assessing, and attesting the learner. We present each of these steps and discuss how leveraging innovative knowledge structures using network science, emerging technologies, and AI, can support the proposed learning system that engages learners in their learning journey. The system's effectiveness is illustrated through two pilot studies on two different learning systems, a process that integrates: (i) a theoretical framework developed based on data on student learning and (ii) on student and faculty experience undergoing years of testing and refinement based on faculty expertise and learners' experiences, shaping the systems' designs and outcomes.

*Keywords:* networks of knowledge, individual learning pathways, personalized education, micro-learning.

## 1. INTRODUCTION AND MOTIVATION

Learning is shaped by how individuals receive, internalize, and use information (Huitt and Hummel, 2003). Factors such as experiences, biases, environments, and cognition influence the way learners engage in the process. Traditional education systems often push knowledge at students through compulsory or comprehensive curricula without ensuring such content has relevance to each student's current needs and competencies. Instead, these systems emphasize a long-term payoff, which can demotivate the learners. Instead, learning should be designed to meet each student's current needs and interests, in a timely manner.

A personalized learning and development system (LDS) must recognize and adapt to each learner's traits. The proposed LDS adjusts content based on three factors: 1) learner competency, to address personal cognitive load and working memory; 2) structuring and organization of learning activities; and 3) ability to control the engagement within a collaborative learning model. Information technology enhances the system by modeling, guiding, motivating, and assessing, The role of network science is emphasized in the creation of personalized learning pathways, using a dynamic network of knowledge as a foundation to design tailored learning experiences. By providing a system that supports self-directed and self-paced opportunities, the LDS meets individual learning goals within a participatory learning environment. Such efforts push the limits of the current educational systems, tools, and a learning system's capabilities to create a personalized educational experience enhancing learning outcome achievement.

## 2. THEORETICAL BACKGROUND

This section synthesizes components of learning science and network science components addressing the extrinsic and intrinsic motivation of learners.

### 2.1. Learning Science

Learning occurs when individuals process, organize, and connect new information to preexisting ideas to create new meaning (Bransford, Brown, & Cocking, 2000). A learner's ability to receive, reflect, and internalize information, within the limitations of working memory and long-term memory, is an important consideration when designing an LDS. If working memory becomes overloaded, learners may struggle to process new information, disrupting the learning process (Cook & McDonald, 2008). Effective content design, including the design of activities, their structure, and the scaffolding and segmentation of content, is an important aspect of managing cognitive load.

Technology supports cognitive load management by using expert-guided instruction and micro-modules, also defined as CHUNKs, with opportunities to check for understanding (Gera, Bartolf, Isenhour, & Tick, 2019). These self-contained modules allow learners to pause naturally, reducing strain on the learner and restoring their ability to take in new information. Adaptive learning tools further personalize the experience by providing learners with critical feedback tailored to their specific challenges.

New learning system use models that automatically identify a learner's working memory capacity by analyzing the learner's behavior within the learning system (Chang, Kurcz, El-Bishouty, Kinshuk, & Graf, 2015). Thus, a personalized LDS would capture learning data, update learner characteristics, and adapt the recommendations presented to the learner. So, the LDS filters suggested content that is most relevant to each learner, mitigating the risk of overwhelming the learner while enabling the LDS to adjust recommendations, filtering learning content (Reith & Dever, 2021).

Learner agency within the personalized Learning Delivery System (LDS) empowers learners by giving them control over their learning process. The LDS would be designed to enhance understanding, ability, and opportunities for learners to take an active role in their education. This approach fosters engagement and reduces the cognitive load on working memory. Discussions of learning schemas as a necessary component of cognitivist learning theory form the basis of this research (Gholson & Craig, 2006). By creating mental representations of interconnected content, learners can establish connections between existing knowledge and new complex knowledge supporting improved retention and storage in long-term memory (Van Merriënboer & Sweller, 2010).

### 2.2. Collaborative Environments

In creating a student-centered learning environment within higher education, the goal is to facilitate learner knowledge creation through experience rather than simply transferring information from subject matter experts to learner. A collaborative environment can support this by encouraging experiential learning, cognitive learning, participatory learning, case studies, discussions, and other problem-solving methods. These approaches leverage pre-existing resources available on the Internet to populate learning pathways (Feldman, Konold, Coulter, & Conroy, 2000). Learners navigate this networked environment as self-directed and self-paced users, supported by asynchronous or synchronous engagements.

The "Network of Knowledge" generates a mind map of concepts, providing an environment where subject matter experts can collaboratively contribute and tag content based on their expertise. This content is then connected in a non-linear way through prerequisites or dependencies, much like a mind map (Cleven, 2018). Existing prototypes already demonstrate real-time adaptive micro-learning methods, enhancing and personalizing education by using particular multimodal engagement for each learner as well as relating the content to each learner's knowledge (Gera, Bartolf, & Isenhour, 2018).

A network science approach to learning addresses the challenges of information overload by guiding students through networked learning pathway recommendations that can screen out the extraneous content and focus the learner on achieving the set goals (while still seeing the connections to the extraneous content if desired). Self-paced learning has been practiced and empirically analyzed using intentional and meaningful learning supported by networked content and activities (Gera et al., 2019). An interconnected model of education introduces a non-linear perspective on knowledge to support its users. Thus, in a network science approach, learning support is modeled as a social network comprised of content creators, instructors, instructional support staff, stakeholders, sponsors, and learners.

## 3. CONTEXT OF THE RESEARCH

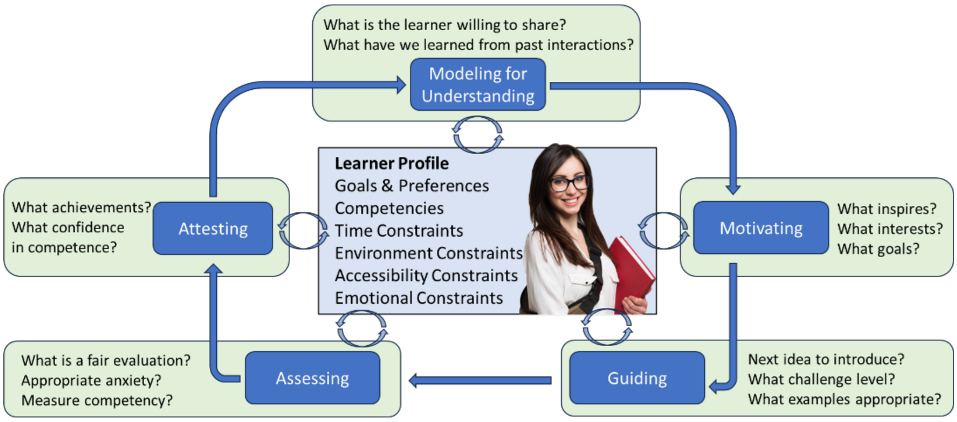
Supported by network knowledge and the network science approaches, the proposed model for personalized learning is designed for a networked environment inspired by existing frameworks. Figure 1 depicts the learning components within a learning cycle and how they inform a learner profile which is subsequently used to support personalized learning.

*The learner profile* is built automatically on data collected about the learner, including education, interests, personality, preferences, employment, and resource accessibility. In formal courses, instructors attempt to elicit some details through student introductions, discussions, and engagement over time, and use the data to scaffold material as they teach. Similarly, an LDS collects and applies this data to personalize the learning experience and content. Personalization can take several forms:

1. Learners may start at an advanced point in the curriculum based on their existing knowledge.
2. Teaching examples and analogies may be customized to align with familiar experiences of the learner.
3. The LDS may adjust teaching strategies based on the learner's attitude toward a topic.

These learner profile categories can be leveraged in the five components shown in Figure 1.

*Figure 1.*
*The Learning Cycle shows activities associated with learning and their interaction with the learner profile.*




*Modeling* the learner often involves assessing prior knowledge through pre-tests, baseline assessments, and inquiries about background experiences. This information supports instructors' and systems' ability to adapt learning content, making it relevant and effective.

The learner profile includes competencies, constraints, and a set of goals. Chief among these competencies is the learning competency that models the proficiency of the learner to achieve goals. Crafting adaptable micro-modules to personalize learning and sequencing them into a personalized pathway requires background information on the learner stored in a learner profile. The ubiquity of data opens the opportunity to shape customized learning experiences by tailoring the curriculum making it efficient compared to commonly observed approaches in today's education, such as one-size-fits-all or differentiated by group level.

*Motivating* the learner includes motivation to start learning a topic and motivation to endure the process to completion. The former may involve such intrinsic motivators as a need to address an immediate issue, seek out a better quality of life, or the pure joy of learning and satisfying curiosity. The latter may involve extrinsic motivators such as grades or demonstration of competency, improved by personalization of learning and supporting learner's meta-cognition. First, to support dual encoding of information through exposure to diverse modalities of interacting with the content, we envision leveraging the learner profile's tags to match appropriate content from the network of knowledge. Second, to support meta-cognition, the LDS provides immediate and specific feedback to each user to have the opportunity to improve self-learning based on the reporting that the environment captures.

*Guiding* the learner is the process of presenting and sequencing learning materials, achieved by using best practices such as spaced repetition, elaboration, visuals, concrete examples, and concept maps. Directed learners are guided individually by learning paths throughout the network of knowledge, ranked ordering all choices of content that meet the same learning outcomes, thus empowering the learner in selecting the depth and breadth of topics. As the motivation for learning changes for more mature learners, to progress towards exploratory learning, the LDS provides choices of content, driven by keyword matching to the learner's profile based on an updated list of keywords from the learned content, based on social networks of the learners (Andriulli, Smith, Smith, Gera, & Isenhour, 2019).

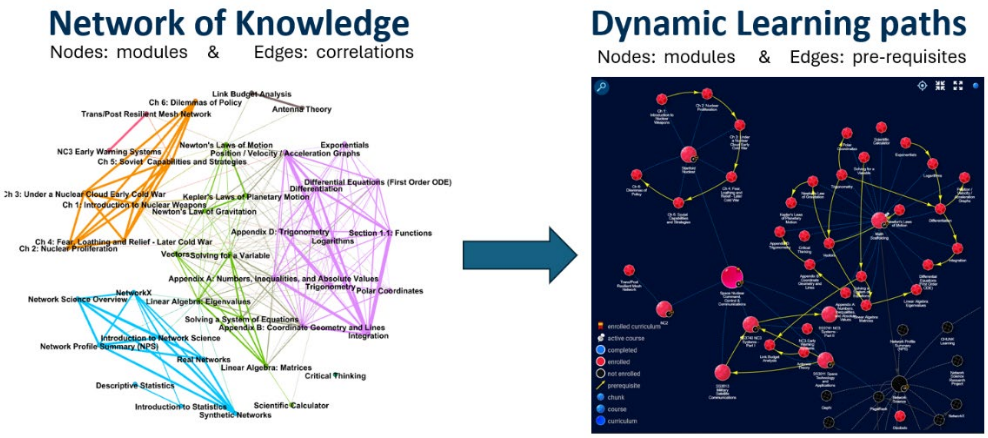
*Assessing* the learner often involves measuring competency, such as adaptive knowledge, skill, ability, behaviors, and characteristics of the learner. Personalized learning depends on granular data for successful agile scaffolding from micro-modules, determining the learner's current state of knowledge and gaps to meet the goals. Such assessments not only provide feedback to a learner's end state at the completion of a learning, but the learner's starting state when engaging in the next activity, guaranteeing relevant learning. *S*tudent-centered assessments that establish evidence about the learning process and validate the competencies achieved, such as formative assessments, support understanding of learning at different instances, continuously monitoring the ability to relate new information with previously acquired principles. Additionally, they provide critical feedback on the effectiveness of the learning pathways and help uncover weaknesses or gaps in understanding.

*Attesting* the learner involves witnessing evidence of competency and certifying the learner. Whether it manifests as a degree, certificate, testimonial, reference, or digital badge, a record of competency helps the community efficiently understand a person's proficiency in a topic. The LDS tracks and provides immediate attestation of the learner's progress to inform her decisions, while the learner progresses through the learning path. Consequently, the educational ecosystem must be dynamic, flexible, and a rich cognitive environment supported by adaptable micro-modules based on the LDS's reporting.

## 4. EXPERIMENTATION

This methodology based on the Learning Cycle, was piloted in a set of master-level courses in statistics and mathematics at the Naval Postgraduate School beginning in 2018. The pilot included 70 graduate students in four master-level courses which included alternative modes of engagement and alternative presenters for each topic needed to be mastered in the course.  A network of knowledge was created for each course, enabling students the content to be connected to support the personalized navigation for each learner based on the learners' profiles, with additional content suggestions provided.  A visual of the network of knowledge is depicted on the left of Figure 2 where nodes represent content modules, and the edges capture similarity based on content-associated tags (thicker edges represent more tags in common).  The right picture of Figure 2 shows learning paths through the network of knowledge on the left, as displayed to the learners.

*Figure 2.*
*A Sample Learning Path is displayed on the right, based on the Network of Knowledge Environment displayed on the left side of the picture.*




Pre- and post-course assessments revealed several key themes. Flexibility emerged as a highly valued aspect across all courses. In the OS3604 statistics course, 90.48% of students found the flexibility in managing study time and content choice helpful or very helpful with similar benefits reported by 85.72% of students in the MA4027 mathematics course The effectiveness of the LDS approach varied significantly by subject. In OS3604, 47.62% of students preferred the blended LDS approach, with 76.19% feeling well-prepared after completing CHUNK modules. In contrast, MA4027 had a lower preference for the LDS approach at 33.33%, with students reporting reduced preparedness.

Self-directed learning was widely encouraged across courses. Both OS3604 and MA4027 saw high usage of alternative modes of engagement for coding, as the LDS provided code in multiple coding languages for the same concept. One student from OS3604 remarked, "I liked how I could go through the material in any order at any time. The progression of the CHUNKs was logical and helped prepare me for future subjects." A student from the OS3307 advanced statistics course shared, "I loved the Matlab, Python and R scripts that she posted. The JMP videos were very helpful too." This idea was generalized to offer content in multiple modes of engaging as well, such as PDF versus Video versus PPT, for example.

The impact of course level on LDS effectiveness was evident. Introductory-level content, particularly in OS3604, benefited more from the LDS approach. In advanced topics, such as those in MA4027, while some students saw a stronger preference for traditional teaching methods, other students still found value in the new approach. One MA4027 student noted, "I prefer CHUNK over face-to-face learning due to the 'learn on your own' approach. I learn best when teaching myself and going to office hours for the things I cannot understand on my own."

The responders from OS3307 advanced statistics highlighted the challenges posed by complex subjects within the LDS framework. Despite significant time investment, only 25% of students felt well-prepared after completing CHUNKs. A student from this course commented, "It would have been a great supplement course but the face-to-face was necessary for this type of course. Which requires a hands-on lab."

These findings indicate that while LDS offers promising flexibility and encourages self-directed learning, its effectiveness varies based on subject matter and course level. As one student aptly put it, "Topics and methodology need to be much smaller in order for this type of course to work. The statistics material is extremely broad with a diverse topic set along with programming skills. CHUNK would work well with broad topics not deep dives into broad topics."

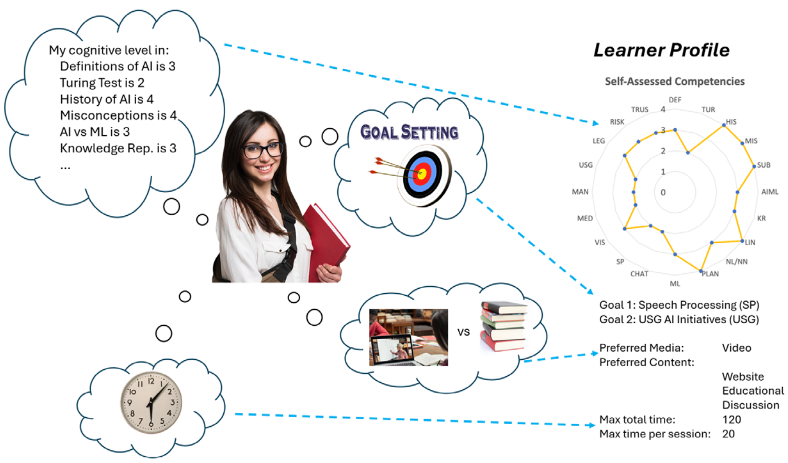
Future developments should focus on tailoring the LDS approach to specific subject needs, particularly for advanced or complex topics. The pilot demonstrates the potential of personalized educational technology while emphasizing the need for nuanced implementation strategies that consider the unique demands of different academic disciplines and levels of study.

## 5. SIMULATION WITH REAL DATA

Contrasting Section 4, this section introduces Learning Paths that complement structured formal classes, highlighting the benefits of using a personalized learning cycle for re-skilling each learner, rather than having all students follow the same topics as presented in Section 4.

The simulation data is based on a survey of Mochocki and Reith of 11 graduate school learners that provided their personal experiences and goal topics for an advanced AI course. We create learner profiles, as shown in Figure 4, by using the survey displayed in Figure 3, which shows just the relevant portion of the survey data used for the simulation. A complete discussion of the data can be found in (Mochocki & Reith, 2024).

*Figure 3.*
*A sample Learner Profile is displayed on the right based on learner's metadata depicted on the left.*




To create learner profiles from the questionnaire data, metadata that supports tailoring educational content to individual needs was prioritized. This includes self-assessments of background knowledge, time constraints, personal goals, and interests.

*Figure 4.*
*A portion of the survey form used for data collection.*

**Cognitive Level Definitions:** Use these definitions when filling out the table below:

**Cognitive Level 1:** A person at this level has very little understanding of the topic and is not familiar with normal terminology, acronyms, or how the concepts fit together.

**Cognitive Level 2:** A person at this level is familiar with the acronyms and the terminology in this topic area but is not able to meaningfully contribute to conversations in this area.

**Cognitive Level 3:** A person at this level is familiar with the acronyms and terminology related to this topic and can contribute to conversations with others who are also familiar with this topic. They are prepared to read technical papers and watch scholastic lectures in this area, even if they do not understand everything they read or hear the first time or need to do additional research to aid in their understanding of some advanced concepts.

**Cognitive Level 4:** A person at this level can understand most materials on this topic, including those that may be technical in nature.

How would you rate your cognitive level (CL) on each of these 20 topics according to the provided scale? Also, indicate **two** goal topics you would choose for a PLP? (mark Y for goal nodes, N otherwise)

| Topic | CL | Goal? | Topic | CL | Goal? |
|---|---|---|---|---|---|
| Definitions of AI and Intelligence | | Y N | Machine Learning in general | | Y N |
| Turing Test and its Improvements | | Y N | Chatbots for user interaction on simple tasks | | Y N |
| History of AI | | Y N | Speech processing | | Y N |
| Misconceptions about AI | | Y N | Computer vision | | Y N |
| Main subareas of AI | | Y N | AI in medicine | | Y N |
| AI versus Machine Learning | | Y N | AI management roles | | Y N |
| Knowledge Representation | | Y N | U.S. Government AI initiatives | | Y N |
| Linear Models | | Y N | Legal issues in AI | | Y N |
| Nonlinear models and neural networks | | Y N | Risks of AI | | Y N |
| Planning and Search | | Y N | Developing trust in AI | | Y N |

Estimate your preferred media type? (circle 1): Video, Written, No Preference

Estimate your preferred content type rank ordered from 1-9? (1 indicates most preferred, 9 least preferred):
Research ___ Educational ___ Do it Yourself ___ Lecture___
Website ___ News Article ___ PowerPoint ___ Textbook Excerpt ___
Discussion ___

Estimate your max time available for committing to completing a PLP (in minutes): _________________

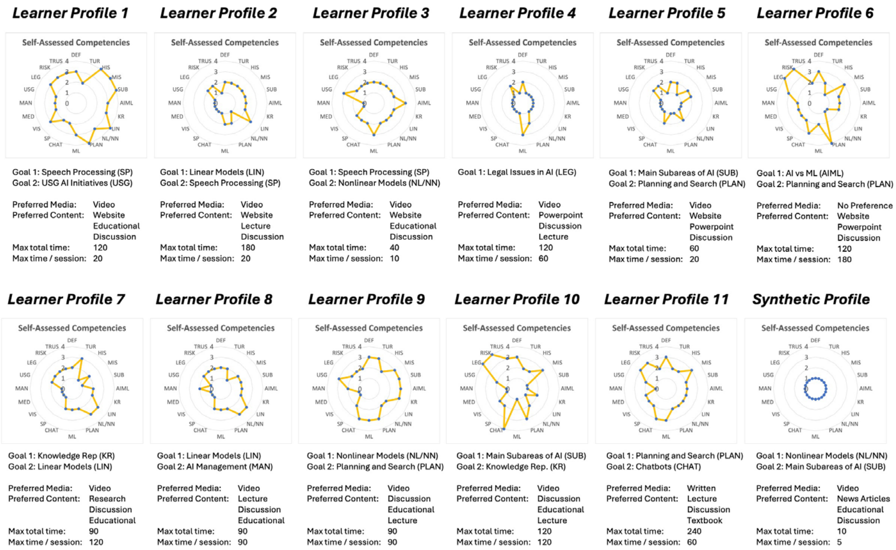
Estimate your max time available per learning session (in minutes): ________________

Please provide any media types, content types, or topics not mentioned above that you might be interested in:

___________________________________________________________________________

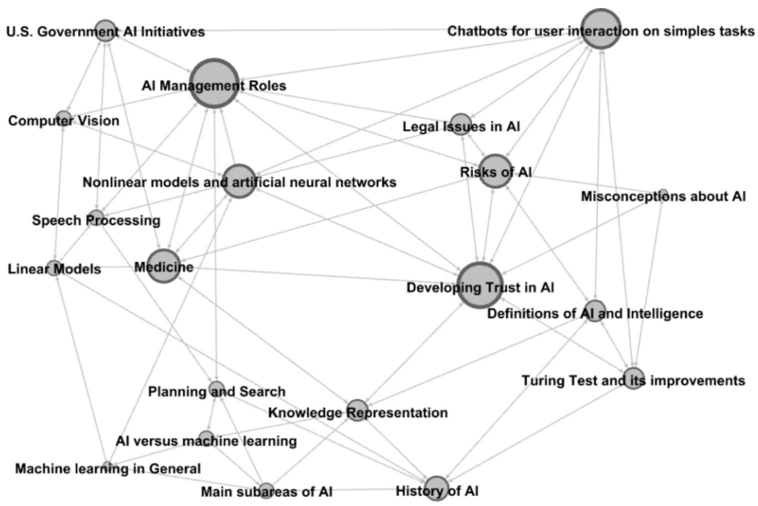
The learner profile data collected using the survey of Figure 4 includes 11 users and their metadata, along with one synthetic profile designed to test a corner case (Mochocki & Reith, 2024) displayed cumulatively in Figure 5.

*Figure 5.*
*The 11 learner profiles and one synthetic profile used in our simulation.*



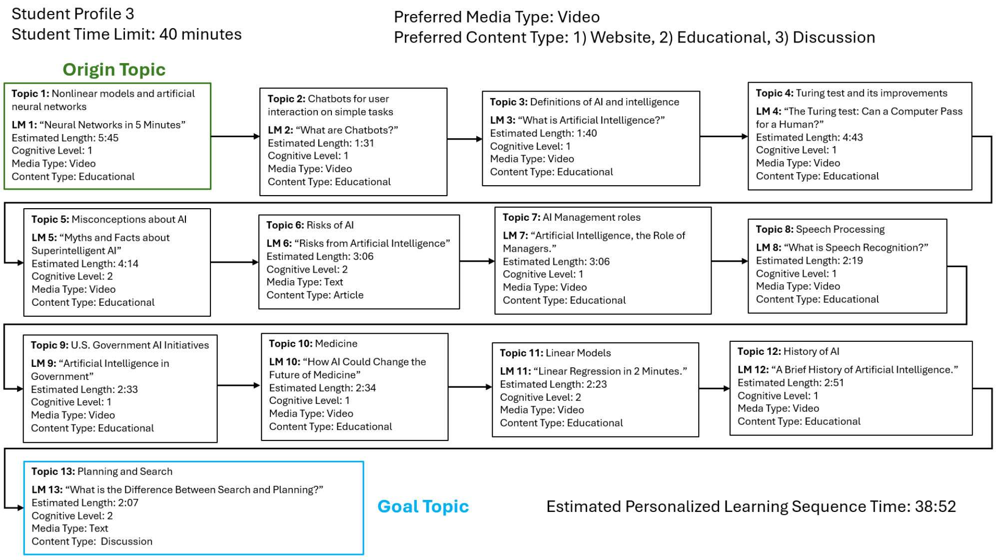

The network of knowledge used for this experiment, is introduced in Figure 6, where nodes represent the AI topics depicted in Figure 4, and the directed arcs capture prerequisite relationships. Double-arrow arcs indicate correlations between topics. The nodes are sized by their number of relationships, thus identifying commonly needed pre-requisites.

*Figure 6.*
*The network of knowledge of the AI topics from Figure 3 (the nodes are the topics, and the arcs capture topical relationships between them).*



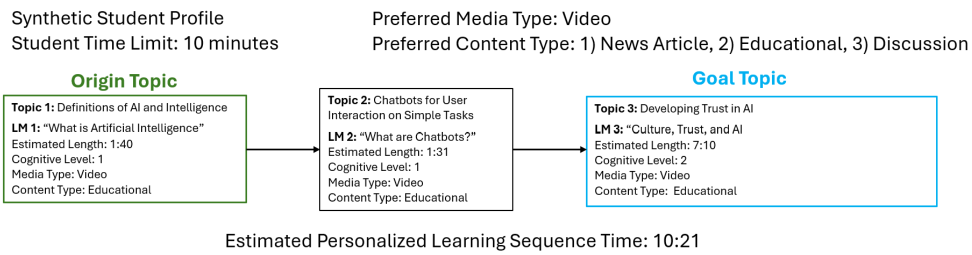
In Figure 7, we display a sample learning path for Student Profile 3 through the network shown in Figure 6. It provides content based on the learner's profile of Student 3, in order to meet the learning goal of the profile. In this approach, learning materials are scored according to whether they match the student's cognitive level for that topic, if they match the student's media preference (video vs written) and how well they match the student's content preferences (DIY, websites, etc). The completion time for learning paths is the sum of the learning materials' time on the path.

*Figure 7.*
*A sample learning path matching the tags of Student Profile 3.*




Since students provided their total available time in the survey, the LDS aim to meet it if possible. The Synthetic student profile has 10 minutes of available time to learn, and the shortest path from origin topic to goal topic is 10 minutes and 21 seconds as shown in Figure 8. And so there is no solution for this student, however, the suggested path is very close the requested one and can be shown as an option for the student's decision. The synthetic profile demonstrates that the expectations cannot always be met, but a near-optimal path with its associated duration can still be proposed.

*Figure 8.*
*A sample "best fit" learning path when there is no solution due to time constraint.*



## 6. CONCLUSION AND DISCUSSION

This work addresses a very important question that whether personalized and individualized learning can occur effectively and efficiently in a learning environment that benefits from advances in technology. The introduced model is centered around the learning cycle of a learner's profile to support personalized learning paths through a network of knowledge, concluding with assessing the competency of the learner. The learning science motivation for this approach is presented, building on the network science framework for personalized education, which uses learning paths of micro-modules derived from a network of knowledge (Gera et al., 2019).

Recommendations for learning paths and assessments can be personalized based on the learner's profile, with content tailored to existing competencies and interests. Results from pilot studies at the Naval Postgraduate School demonstrate the benefits of this model. We complement this study by present real learner profiles and simulations showcasing the creation of personalized learning paths based on these profiles are included, highlighting the possibilities this approach offers.

Future explorations could focus on incorporating Artificial Intelligence (AI) to leverage emerging technologies. In education design, AI can support both the network curators and learners, since knowledge identification, curation, and uploading is time-consuming. For example, an automated way of updating the network of knowledge's learning materials creates a dynamic (vice static) network construct would enable a collaborative growth of the knowledge (Singh & Gera, 2024). Additionally, AI-agents could complement the current learning experience and work towards shortening the time required for students to learn the same skill efficiently (Mochocki et al., 2024).

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## ACKNOWLEDGEMENTS

Gera, Mochocki, Reith, Singh, & Tick thank the DoD and Department of Veterans Affairs for sponsoring this work.

## AUTHORS' INFORMATION

**Full name:** Ralucca Gera
**Institutional affiliation:** Applied Mathematics Department, Naval Postgraduate School
**Institutional address:** 1 University Way, Monterey, CA, 93943, USA
**Short biographical sketch:** Dr. Ralucca Gera, a distinguished graduate of Western Michigan University, is a Professor of Mathematics at the Naval Postgraduate School, serving as the Applied Mathematics Academic Chair, Director of CHUNK Learning, and Program Manager of the Network Science Academic Certificate. A forward thinker, she is a leader in the classroom and research, with an education strategy focused on quality, effectiveness, and innovation in the T&L experience through intentional learning. She emphasizes exploration and experimentation, empowering students to be confident learners by cultivating curiosity and inquiry while taking ownership of their learning. She lead the NPS' transition to Online T&L during the pandemic, and the Distance Learning Quality Initiate that developed educational resources and experiences emphasizing course quality and cohesive learning experiences. Additionally, she lead innovation education research projects such as Classroom of the Future, Campus of the Future, the Future of Learning, and she is the Educational Lead for ASPIRE.

**Full name:** Mark G. Reith
**Institutional affiliation:** Department of Electrical and Computer Engineering, Air Force Institute of Technology
**Institutional address:** 2950 Hobson Way, Wright-Patterson Air Force Base, OH 45433-7765
**Short biographical sketch:** Mark Reith received a B.S. degree in Computer Science from the University of Portland, Portland, OR, USA, in 1999, a M.S. degree in Computer Science from the Air Force Institute of Technology, Wright-Patterson Air Force Base, OH, USA, in 2003, and a Ph.D. degree in Computer Science from the University of Texas at San Antonio, San Antonio, TX, USA, in 2009. He served over 20 years in the U.S. Air Force as a communications and cyber officer. He currently serves as an Assistant Professor of Computer Science with research interests in learning technologies, cyber education, software/systems engineering and modeling.

**Full name:** D'Marie E. Bartolf
**Institutional affiliation:** QuantHub
**Institutional address:** Birmingham, AL, USA
**Short biographical sketch:** D'Marie Bartolf earned her Ed.D. in Leadership and Learning in Organizations from Vanderbilt University, Nashville, TN, USA, in 2023. She currently serves as the VP of Curriculum at QuantHub, an education technology company specializing in data literacy and data science. Passionate about enhancing learning environments to meet modern educational needs, D'Marie is dedicated to transforming teaching and learning methods. Prior to joining QuantHub, she was a faculty associate at the Naval Postgraduate School (NPS), where she focused on researching the design of adaptive learning spaces and personalized learning and development systems. Her diverse experience includes serving as a faculty member and Department Chair of the Naval Science Department at California State University Maritime Academy. Additionally, D'Marie has a background as a Naval Flight Officer, having operated in the EA-6B Prowler.

**Full name:** Simona Tick
**Institutional affiliation:** Department of Defense Management, Naval Postgraduate School
**Institutional address:** 1 University Way, Monterey, CA, 93943, USA
**Short biographical sketch:** Dr. Simona Tick earned her Ph.D. in Economics from the University of Arizona, with a focus on labor economics and applied microeconomics. At NPS, Simona teaches graduate courses on data science applications to manpower and personnel economics, linear optimizations and simulations, and resource allocations. Simona's teaching was recognized with several awards. Her passion for innovation in education inspired her to focus on assessments of engagement, learning and experiences in different learning environments. She is an NPS Teaching Fellow, and currently serves as Associate Chair for Instruction in the Department of Defense Management.

**Full name:** Paolo J. Singh
**Institutional affiliation:** Applied Mathematics Department, Naval Postgraduate School
**Institutional address:** 1 University Way, Monterey, CA, 93943, USA
**Short biographical sketch:** Paolo J. Singh is a Ph.D. Student with the Applied Mathematics Department at the Naval Postgraduate School. His research interests include network science, statistics, combinatorics, and both the art and science of pedagogy—specifically toward math and STEM exposition at all grade levels. Following his program completion, he intends to join the NPS Operations Research faculty. Singh graduated from the United States Naval Academy in 2003 with a bachelor's degree in Mathematics, and from Johns Hopkins University in 2022 with a master's degree in Applied and Computational Mathematics. Additionally, he is a 2010 graduate of the U.S. Navy Fighter Weapons School (TOPGUN), which emphasizes excellence in the teaching and learning of navy fleet practitioners.

**Full name:** Sean A. Mochocki
**Institutional affiliation:** Department of Electrical and Computer Engineering, Air Force Institute of Technology
**Institutional address:** 2950 Hobson Way, Wright-Patterson Air Force Base, OH 45433-7765
**Short biographical sketch:** Sean Mochocki is a Computer Science PhD student in the Air Force Institute of Technology (AFIT). He received a B.S. in Mechanical Engineering in 2006 and a B.S. in Electrical Engineering in 2012 from the University of North Florida in Jacksonville, FL, along with an M.S. in Computer Science from AFIT in 2020. Sean is currently an active-duty major in the United States Space Force, serving as an acquisition engineer. Sean's research interest includes personalized learning paths, artificial intelligence, machine learning, computational complexity, and learning technologies.

**Full name:** Akrati Saxena
**Institutional affiliation:** Leiden Institute of Advanced Computer Science, Leiden University
**Institutional address:** Gorlaeus Gebouw, Einsteinweg 55, 2333CC, Leiden, the Netherlands
**Short biographical sketch:** Dr. Akrati Saxena is an assistant professor at the Leiden Institute of Advanced Computer Science, Faculty of Science at Leiden University. Before joining Leiden University, she worked as a Research Fellow at NUS, Singapore and Eindhoven University of Technology, Netherlands. Her research interests include Social Network Analysis, Complex Networks, Computational Social Science, Data Science, and Fairness. Her current research is focused on understanding societal inequalities and using that to design fair algorithms for network and data science.