Leveraging Intelligent Tutoring Systems to Enhance Project-Based Learning in Workforce Training at Community Colleges

Marshall An(✉), Leah Teffera, Mahboobeh Mehrvarz, Bruce Li, Christopher Bogart, Majd Sakr, and Bruce M. McLaren

Carnegie Mellon University, Pittsburgh PA 15213, USA
{haokanga,lteffera,mmehrvar,bnli,cbogart,msakr,bmclaren}@andrew.cmu.edu

Abstract. To meet the growing demand for IT and cybersecurity professionals, community colleges in the United States face the challenge of enhancing workforce training within their resource constraints. Reflecting on an online Project-Based Learning (PBL) training pathway for cloud administrator jobs developed with community colleges, we acknowledge PBL's value while also noting its overheads. To explore more efficient approaches for training fundamental skills, we integrated Intelligent Tutoring Systems (ITS) with PBL. Through curriculum analysis, we identified areas where ITS functionality could be particularly beneficial. A collaborative effort between learning scientists, subject matter experts, and instructors led to the development of an ITS tailored for essential cloud administration skills. We conducted a pilot study with six participants to preliminarily assess its efficacy. This randomized controlled trial compared ITS with a control group using reading materials and multiple-choice questions. Given the very small sample size, we interpret our results with caution. Despite these limitations, we observed a discernible improvement in post-test performance for participants using ITS compared to those in the control condition. Encouraged by these findings, we plan to expand the adoption of ITS in IT and cybersecurity workforce training at community colleges. Our goal is to facilitate a seamless transition for students from foundational training to practical application, thereby improving their technical skills and career readiness.

Keywords: Intelligent Tutoring Systems · Project-Based Learning · Students Learning · Community Colleges · Workforce Training · Feedback · IT Education

1 Introduction

Addressing the growing demand for information technology (IT) and cybersecurity professionals in the United States, community colleges play a pivotal role in

R. Ferreira Mello et al. (Eds.): EC-TEL 2024, LNCS 15160, pp. 57–62, 2024.
https://doi.org/10.1007/978-3-031-72312-4_5

advancing workforce training despite limited resources. Problem solving is a fundamental competency across various science, technology, engineering, and math (STEM) careers [6,11]. Project-Based Learning (PBL) emerges as an effective pedagogical strategy that fosters problem-solving skills and career readiness. In PBL, learners acquire knowledge and skills by developing end products that solve real-world problems over an extended period [2,4,8]. In collaboration with community colleges, we have devised an online PBL training pathway towards career readiness for cloud administrator jobs. During this online PBL, students complete hands-on tasks addressing real-world challenges using commercial cloud platforms such as Microsoft Azure, supported by an autograding system that provides timely and contextual feedback to their solutions.

Reflecting on our successful PBL course offerings with 33 partner colleges, we acknowledge the value of PBL in workforce training but also its associated challenges. Students encounter both cognitive and time overheads when engaging with real-world cloud platforms. The cognitive overhead arises from the complexity of these platforms, which offer a comprehensive range of products with extensive features and configurations. While this diversity caters to various professional needs, students must navigate through an overwhelming array of options within the cloud platforms' web interfaces to find relevant products and settings. Time overheads occur during actions such as creating, updating, and terminating cloud resources. These processes require time to take effect, leading to lengthy waits between task attempts, disrupting the learning flow and reducing the efficiency of the training. While the ultimate training goal is for students to apply their skills to real-world cloud platforms, we want to explore instructional methods that can provide the initial training of many fundamental skills in a more efficient manner.

These observations have directed our attention towards Intelligent Tutoring Systems (ITS), which have demonstrated significant efficacy in various educational settings through decades of rigorous research and established best practices for their design and implementation [1,13–15]. We decided to investigate the following research questions:

RQ1: Is ITS an effective and efficient teaching method for fundamental skills in the domain of IT and cybersecurity?

RQ2: What is the impact of ITS on subsequent PBL experience?

RQ3: Is the efficacy of ITS attributed to the teaching method itself or to the content delivered?

2 Research Design

2.1 Instructional Design of ITS

Curriculum Mapping for ITS Design. The existing online PBL training for cloud administrator roles consisted of eight hands-on projects focusing on a range of practical technical skills, including the provisioning, orchestration, scaling, management, and monitoring of cloud services. We needed to decide where ITS could best support PBL and what learning objectives to target, which prompted us to employ the curriculum mapping method. Curriculum mapping is a strategic approach to coherent and cumulative progression of knowledge and skills within a discipline, by evaluating and aligning course content with desired learning outcomes [5,12]. We further deconstruct the learning objectives into knowledge components (KCs), which are discrete cognitive functions attainable through learning events and observable through assessments [7]. The Knowledge-Learning-Instruction (KLI) framework categorizes KCs based on their complexity into Memory/Fluency (M), Induction/Refinement (I), and Sense-making/Understanding (S) [3,7]. Research has shown that (I)-type KCs are well suited with ITSs [9,10]. Therefore, our ITS was designed to primarily focus on (I)-type KCs, while incorporating necessary (M)-type and (S)-type KCs. Table 1 demonstrates that the KCs, though discrete and separately trainable, must be integrated and applied collectively to address real-world job tasks.

Table 1. KCs based on expert cognitive models solving cloud scalability job tasks.

Example Knowledge Components (KCs)	KC Type
Analyze infrastructure utilization	(I)
Decide on resource adjustments	(I)
Identify applicable scaling methods	(I)
Justify the preference for horizontal scaling over vertical scaling	(S)
Implement a chosen scaling method	(I)

ITS Implementation and Refinement. As Fig. 1 illustrates, the ITS was designed to systematically break down expert cognitive models, guiding learners to replicate how experts tackle real-world job tasks. Figure 2 showcases the ITS's provision of multiple levels of hints at each step. The ITS design was refined using feedback from pre-pilot testing with 6 university students.

2.2 Pilot Research Study

Experiment Design. To answer the RQs, we conducted an in-vivo experiment to compare ITS with a control condition within the context of a community college course offering, as depicted in Fig. 3. A total of 6 students consented to participate in and completed the study. The pilot study, structured as a randomized controlled trial, included a pre-test, an intervention phase where participants were randomly assigned to either ITS or Reading+MCQs, followed by a post-test and a survey. To assess learning gains, we developed two equivalent yet distinct 17-question quizzes for the pre- and post-tests. Upon completing the research components, participants proceeded to complete the hands-on project as per the course's regular curriculum. The control condition, which consisted of reading materials and multiple-choice questions (MCQs), was deliberately designed to mirror the same expert cognitive models and to cover all the KCs present in ITS. Table 2 contrasts PBL, ITS, and Reading+MCQs.

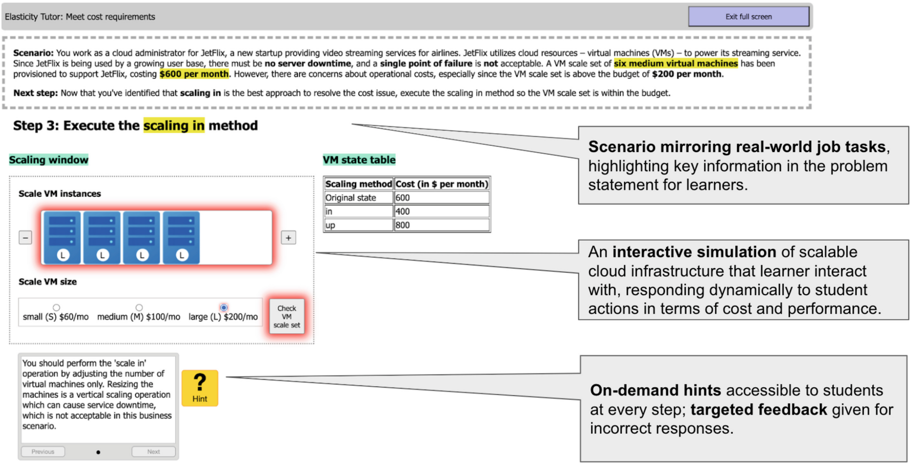

Fig. 1. ITS interface. Key features are highlighted with annotations.

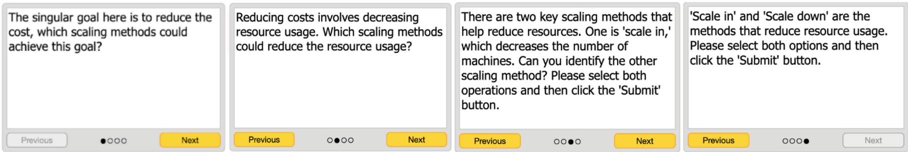

Fig. 2. Provision of multiple levels of hints at each step.

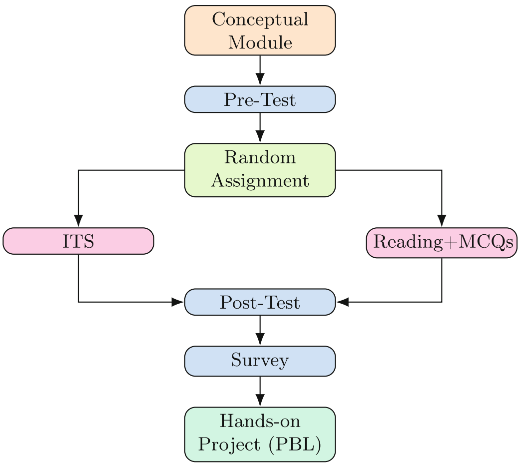

Fig. 3. Research study design.

Table 2. Comparison of instructional methods: PBL, ITS, and Reading+MCQs

Feature	(Existing) PBL	(Experimental) ITS	(Control) Reading+MCQs
Cloud Infrastructure	Real-World Usage	Interactive Simulation	Static Screenshots
Cloud Platform	Specific	Agnostic	Specific/Agnostic
Practice Overhead	Moderate	Low	Low
Feedback Scope	Final Solution	Problem-Solving Steps	MCQ Correctness
Feedback Timeliness	Near-Instant	Instant	Instant

Data Analysis. Pre- and post-test scores were analyzed. The Shapiro-Wilk test confirmed normality in score differences for both ITS and control groups, supporting the use of paired sample t-tests. The ITS group showed significant post-test improvement ($t(2) = 5.199$, $p = 0.035$), unlike the control group ($t(2) = 0.866$, $p = 0.478$). ANCOVA, using pre-test scores as a covariate, indicated no significant difference in pre-test scores between groups ($p = 0.188$), indicating a fair comparison basis. Controlling for pre-test scores, ANCOVA revealed a significant effect of the condition on post-test scores ($p = 0.0119$). In addition to effectiveness, we also assessed efficiency by comparing the time-on-task. Although students with ITS spent less time on average, an independent t-test revealed no statistically significant difference. We also assessed subsequent PBL experience post-intervention. First, student scores in the project revealed no difference, as all participants achieved a perfect score on the project. This can be attributed to our PBL method, which provided autograded feedback and allowed unlimited attempts. Second, the number of failed attempts before reaching a full score showed no significant group differences.

3 Conclusion and Future Work

This paper presents preliminary evidence on the benefits of integrating ITS with PBL to enhance workforce training. Given the constraints of a small sample size, we approached the interpretation of results with due caution. Despite these limitations, the initial findings are encouraging, particularly the discernible improvement in post-test performance. Next, we aim to replicate the randomized controlled trial with a larger sample size, to further evaluate the effectiveness and efficiency of ITS and its impact for PBL. In addition, we plan to investigate the impact of incorporating task-loop adaptivity [13,14] that automatically selects subsequent problems. Furthermore, we plan to investigate the complementary relationship among computer-supported collaborative learning (CSCL), ITS and PBL. Our goal is to facilitate a seamless transition for learners from foundational training to high-order thinking and practical application, thereby improving career readiness.

Acknowledgments. This material is based upon work supported by the National Science Foundation, under Grant No. 2222762. Any opinions, findings, and conclusions or recommendations expressed in this material are those of the author(s) and do not necessarily reflect the views of the National Science Foundation.

References

1. Aleven, V., et al.: Example-tracing tutors: intelligent tutor development for non-programmers. Int. J. Artif. Intell. Educ. **26**, 224–269 (2016)
2. Blumenfeld, P.C., Soloway, E., Marx, R.W., Krajcik, J.S., Guzdial, M., Palincsar, A.: Motivating project-based learning: sustaining the doing, supporting the learning. Educ. psychol. **26**(3–4), 369–398 (1991)
3. Carvalho, P., Rachatasumrit, N., Koedinger, K.R.: Learning depends on knowledge: the benefits of retrieval practice vary for facts and skills. In: Proceedings of the Annual Meeting of the Cognitive Science Society, vol. 44 (2022)
4. Guo, P., Saab, N., Post, L.S., Admiraal, W.: A review of project-based learning in higher education: student outcomes and measures. Int. J. Educ. Res. **102**, 101586 (2020)
5. Joyner, H.S.: Curriculum mapping: a method to assess and refine undergraduate degree programs. J. Food Sci. Educ. **15**(3), 83–100 (2016)
6. Karan, E., Brown, L.: Enhancing student's problem-solving skills through project-based learning. J. Probl. Based Learn. Higher Educ. **10**(1), 74–87 (2022)
7. Koedinger, K.R., Corbett, A.T., Perfetti, C.: The knowledge-learning-instruction framework: bridging the science-practice chasm to enhance robust student learning. Cogn. Sci. **36**(5), 757–798 (2012)
8. Markham, T.: Project based learning a bridge just far enough. Teach. Libr. **39**(2), 38 (2011)
9. McLaren, B.M., DeLeeuw, K.E., Mayer, R.E.: Polite web-based intelligent tutors: can they improve learning in classrooms? Comput. Educ. **56**(3), 574–584 (2011)
10. McLaren, B.M., Lim, S., Koedinger, K.R.: When and how often should worked examples be given to students? New results and a summary of the current state of research. In: Proceedings of the 30th Annual Conference of the Cognitive Science Society, pp. 2176–2181 (2008)
11. Netwong, T.: Development of problem solving skills by integration learning following stem education for higher education. Int. J. Inf. Educ. Technol. **8**(9), 639–643 (2018)
12. Okojie, M.U., Bastas, M., Miralay, F.: Using curriculum mapping as a tool to match student learning outcomes and social studies curricula. Front. Psychol. **13**, 850264 (2022)
13. VanLehn, K.: The behavior of tutoring systems. Int. J. Artif. Intell. Educ. **16**(3), 227–265 (2006)
14. VanLehn, K.: Regulative loops, step loops and task loops. Int. J. Artif. Intell. Educ. **26**, 107–112 (2016)
15. Woolf, B.P.: Building Intelligent Interactive Tutors: Student-centered Strategies for Revolutionizing E-learning. Morgan Kaufmann (2010)