Community College Information Technology Education: Curriculum Mapping, a Learning Science Framework, and AI Learning Technologies

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Abstract. Most jobs in the digital economy require 4-year university degrees, excluding many community college students. To help these students join the digital economy, our project team is developing AI-based learning technology using a novel approach. First, we employ curriculum mapping to analyze courses and identify knowledge components (KCs) that are positioned to impact student outcomes. We triangulate our results using student learning data and expert-provided qualitative assessment. We then employ the Knowledge, Learning and Instruction framework to align KCs with individual tutoring and collaborative learning. This analysis is guiding us in developing intelligent tutors and collaborative learning technology, empirically-tested forms of AI-based learning technology, to support IT students. In this paper, we describe our innovative approach and results thus far.

1. Introduction

In a changing American labor market, the digital economy remains a powerful locus of growth and opportunity. Unfortunately, most jobs in this sector have been reserved for workers with 4 or more years of university education, which permanently excludes most American adults from these opportunities, especially those who come from disadvantaged backgrounds.

Community colleges offer accessible and affordable IT degrees and certificates, making it feasible for a more diverse demographic to access digital economy jobs (Sergeyev et al., 2019; Sublett & Tovar, 2021). However, it can be challenging for community colleges to provide the learning support their diverse student bodies often require. Our project supports community college IT education by applying learning science theory and evidence-based learning tools at key points in the curriculum.

To minimize cost and maximize the impact of developing learning technology, we first identified individual skills and concepts that (1) are required at multiple points throughout the curriculum, (2) scaffold student learning throughout the curriculum, and (3) are difficult for students to master. We then used *curriculum mapping* to analyze and identify relationships among skills and student learning objectives in a community college curriculum (Cambridge University Press

& Cambridge Assessment, 2020). Next, we used a learning science framework, the Knowledge, Learning and Instruction framework (KLI) (Koedinger et al, 2012), to classify knowledge components and match them with the specific types of learning technologies best suited to helping students learn those KCs. KLI classifies KCs according to the cognitive/instructional categories of memory, fluency, induction, refinement, sense making and understanding. Learning technologies such as intelligent tutors and collaborative learning technology are two approaches that can address KLI-classified KCs.

To be effective these technologies require implementation strategies that consider the human and curricular contexts of instruction. We are therefore collaborating with IT instructors at the Community College of Allegheny County (CCAC) to tailor learning technologies to students at this institution (two instructors are co-authors of this paper). In the following sections, we describe how we have employed curriculum mapping, the KLI framework, and learning technology to help community college students be successful IT workers.

2. The KLI Framework

We apply the KLI framework to community college IT courses, mapping the knowledge components in these courses into the **MIS** spectrum – (**M**)emory/Fluency, (**I**)nduction/Refinement, and (**S**)ense Making/Understanding – which orders learning processes from least to most complex. We are also using KLI to select the best learning technology for each KC. Empirical work building on KLI demonstrates that **M** KCs generally do not benefit from the use of AI-driven learning technologies. However, research has generally shown that intelligent tutoring systems (ITS - McLaren et al., 2008; 2011; 2016; VanLehn, 2011) can provide very effective support for **I** (induction and refinement) KCs and that computer supported collaborative learning technologies (CSCL - Cress et al., 2021; Koschmann et al., 2005) can provide powerful support for **S** (sense making and understanding) KCs.

Ultimately, we intend to use KLI to guide the selection and integration of ITS and CSCL technologies in IT courses at CCAC. The research question we ask is:

> Can we use curriculum mapping and the KLI framework to optimize EdTech development for community college IT courses by identifying and mapping high-value KCs along the **MIS** spectrum?

We believe our work will significantly improve student retention and academic progress in community college IT programs.

3. Overall Approach

Our overall approach is illustrated in Figure 1. We will support and enhance community college IT programs through the design, development and deployment of intelligent tutoring systems (ITS) and computer-supported collaborative learning (CSCL) technologies. The deployment of these technologies will be guided by curriculum mapping and the KLI framework. The impact of our technology and instructional practices on student learning, relative to the standard curriculum, will be measured through randomized controlled trials (RCT) conducted with community college students.

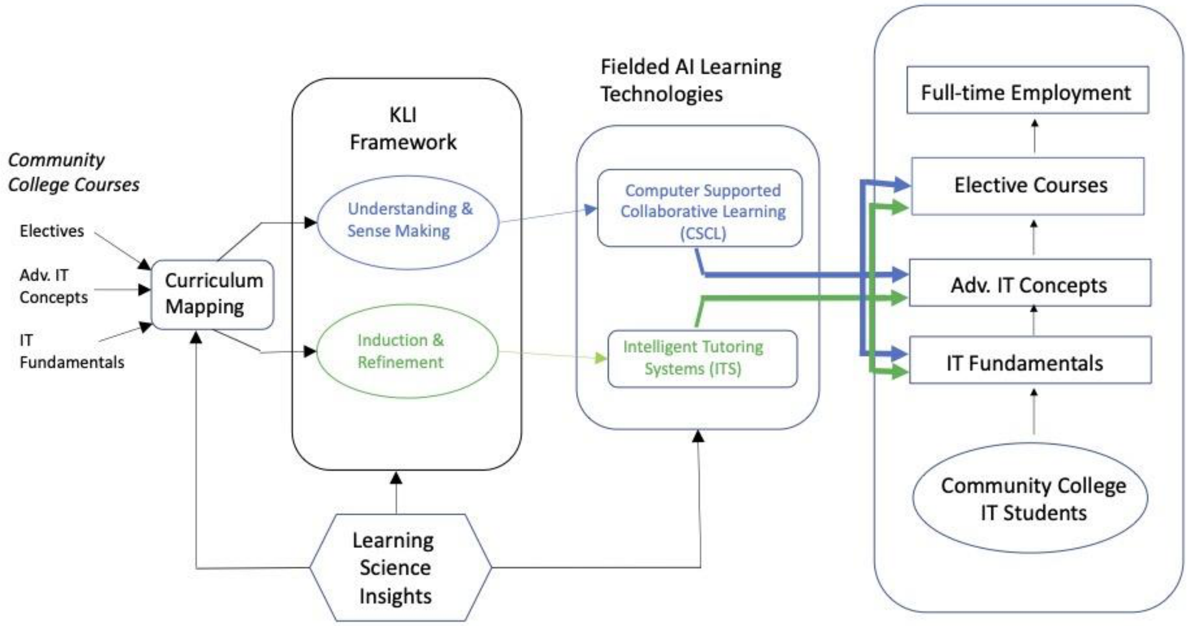


Figure 1: Using Curriculum Mapping, the KLI Framework, and Empirically-tested AI Learning Technologies to Support Community College IT Education

The KLI framework described above will help us classify the KCs of individual IT courses into those parts of the **MIS** spectrum that require induction and reasoning, marked in green in Figure 1, and are (typically) best supported by ITS (e.g., Induction & Refinement), and those parts requiring sense-making and understanding, marked in blue in Figure 1, which are (typically) best supported by CSCL (i.e., Understanding & Sense Making).

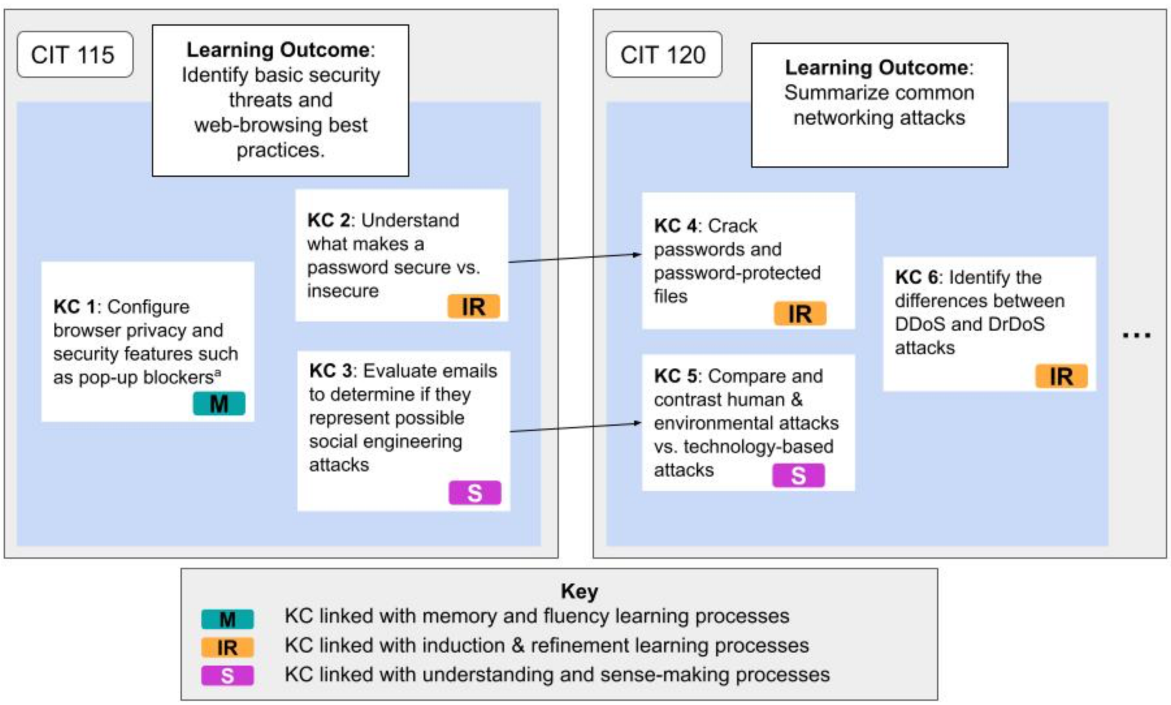
Intelligent tutoring systems (ITS - VanLehn, 2011) are increasingly becoming part of both in-person classroom and on-line learning, with tens of thousands of students using computer-based tutors every year (Kulik & Fletcher, 2016; Mousavinasab et al., 2021; Xu et al., 2019). In one large-scale RCT, an intelligent tutoring system was shown to double the rate of students learning math (Pane et al., 2014). ITS is designed to complement traditional classroom teaching, providing students with a personalized learning experience using AI that is tailored to their individual prior knowledge and learning trajectory. In this project we have begun developing intelligent tutors to help community college students master specific KCs in their courses, guided by the approach shown in Figure 1.

Our project will also support and accelerate community college student learning by harnessing the power of students teaching and learning from one another -- especially when opportunities for collaborative learning are structured and scaffolded (Fischer et al., 2013). Prior experimental studies have demonstrated that AI can significantly expand and enrich these collaborative learning opportunities (Adamson et al., 2014; Kumar & Rosé, 2011; Rosé, 2018). In a landmark paper, Rosé and her collaborators documented learning gains of 1.24 standard deviations when college-aged students utilized digital tools that fostered online collaborative learning (Kumar et al., 2007).

4. Curriculum Mapping

The importance of curriculum mapping has been established in a variety of fields, including library science (Archambault & Masunaga, 2015), social studies (Okojie et al., 2022), and the health sciences (Watson et al., 2020). Most curricula naturally have gaps, redundancies, and misalignments due to the organic way in which a curriculum is often developed. Curriculum mapping is typically used to assess relationships among elements of a curriculum in order to identify misalignments or opportunities for curricular change.

We have used curriculum mapping to identify *relationships* among course-level student learning outcomes across a community college IT curriculum. Specifically, we used curriculum mapping to identify KCs that are required at multiple points throughout the program, are scaffolded to promote longitudinal progression, and which pose a challenge for students. This process is exemplified in Figure 2, in which we show a small snippet of the curriculum mapping and subsequent application of the KLI framework to two courses.



[a] Text for the CIT 115 and CIT 120 KCs is drawn from the TestOut IT Fundamentals textbooks (*TestOut IT Fundamentals Pro*, 2023; *TestOut Network Pro*, 2023)

Figure 2: An example of applying curriculum mapping and the KLI Framework to parts of two CCAC courses

5. Methods

An educational design faculty expert, supported by other members of our team, collaborated to conduct a partial retrospective curriculum map (Watson et al. 2020) of key courses at CCAC.

Our first step in this process was to identify eight courses in CCAC's cybersecurity and IT curriculum that are essential for meeting the five specified IT program-level learning goals. These courses and their 60 course-level learning outcomes were used to map relationships throughout the program and to identify core programmatic requirements in sequence. These courses included, for instance, CIT 115 (IT Fundamentals), CIT 120 (Networking Concepts), and CIT 182 (Principles of Cybersecurity). Each course requires another as a prerequisite – for example, CIT 120 requires CIT 115 – and the later courses build on skills developed in earlier courses.

Student learning outcomes for each of these courses were mapped to indicate scaffolding for progress across the curriculum. For instance, in Figure 2, two key learning outcomes are "Identify basic security threats …" (from CIT 115) and "Summarize common networking attacks" (from CIT 120). These outcomes, if targeted early in the curriculum, have the potential to impact student outcomes throughout the program. For instance, as shown in Figure 2, "Identify basic security threats …" and "Summarize common networking attacks" were identified as learning outcomes that entail longitudinal progression of mastery.

The learning outcomes were, in turn, decomposed into diverse KCs that are also related across courses and evaluated for alignment and longitudinal progression. For instance, KC 3 ("Evaluate emails…") of CIT 115 is typically mastered as a prerequisite to KC 5 ("Compare and contrast …") of CIT 120. CCAC collaborators confirmed the resulting list of KCs as appropriately aligned, elaborated our map to include additional outcomes and relationships, and identified the KCs that are particularly challenging based on past student performance data. A structured analysis of syllabi, required textbooks, learning activities, and certification requirements produced a comprehensive list of KCs associated with learning and assessment activities in the required courses. These were evaluated for conceptual relationships and organized into a flow chart-style map of all KCs. This complex visual map was reduced to include only KCs that scaffold student learning for longitudinal progression. A visual map detailing student learning opportunities associated with each KC was shared with instructors for evaluation and refinement (Balzer, Hautz et al. 2016). The outputs of this process included diverse KCs which were then compared against student learning data from prior years. The KCs for which students demonstrated lower levels of mastery were selected as the primary focus of our project.

Finally, we applied the KLI framework to identify which of the KCs lend themselves to specific learning technologies. For instance, KC 3 and KC 5 were both identified as Understanding and Sensemaking KCs. From a design perspective, then, both of these KCs are likely best addressed through CSCL. We also identified Induction and Refinement KCs in both CIT 115 and 120 – see several shown in Figure 2 – which are likely best addressed through ITS. This curriculum mapping approach has been applied across the IT curriculum to maximize instructional impact. Using our team's deep expertise in ITS and CSCL research and development, we have begun to develop the technologies that will support student learning of the key and challenging concepts and skills faced by community college IT students.

6. Conclusions

Our innovative approach to optimizing learning technology development is well under way, beginning with the challenging qualitative work of curriculum mapping. This was employed to identify knowledge components that recur and scaffold longitudinally throughout a curriculum and where students can be supported by AI learning technologies. We then distinguished between KCs where ITS would most likely be the best choice from those where CSCL would likely be optimal. We also targeted core skills that students struggle to master and that are relevant in multiple contexts across the curriculum. Thus, we are now focusing our efforts on the most promising opportunities for technical development.

Yet, questions still remain about the distinction between knowledge components and the appropriate learning technology to apply to them. There is a dearth of research on this issue, particularly in higher education, where the space of KCs is less worked out than, for instance, in K-12 courses. In addition, many KCs may contain elements of *multiple* aspects of the **MIS** spectrum. Thus, there is still experimental work to be done to refine the theoretical foundation of KLI. To address our primary research question, we are now designing and developing both intelligent tutoring and collaborative learning approaches, guided by our curriculum mapping. Initially, we will develop both technologies to help students learn the same KCs. We will then run RCTs to compare the learning outcomes of students in each of these conditions. This will help us pinpoint which of the complex, ambiguous KCs are better addressed by ITS and which are better addressed by CSCL. Thus, besides helping us answer our project's core research question, this study will add to the lacking empirical literature supporting the KLI theory, particularly in higher education.

Ultimately, our practical goal is to provide a stronger educational approach to community college IT courses, so that two-year college students will be much better equipped to participate and excel in the digital economy. This, in turn, will help address the systemic inequalities limiting job opportunities in this dynamic sector for those without four-year degrees.

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