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Evaluating Private Artificial Intelligence (AI) Curriculum in Computer Science (CS) Education: Insights for Advancing Student-Centered CS Learning

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Abstract: This study was undertaken to pilot a Private AI curriculum designed with a problem-centered instruction (PCI) approach for post-secondary Computer Science (CS) education. To this end, a condensed version of one of the ten curricular modules was implemented in a two-hour workshop. The mixed-method data analysis revealed participants' positive motivation and interest in the curriculum, while also pinpointing opportunities to further improve the design strategies of the curriculum.

Pilot test of a private AI curriculum

This study pilot-tested a Private AI curriculum grounded in the PCI framework, designed to prepare the next generation of AI professionals with a focus on privacy at the post-secondary level. To achieve this, we facilitated a workshop where a scaled-down version of the curricular module was deployed. The study aimed to investigate learners' perceived levels of motivation and interest and to examine collaborative problem-solving behaviors to continuously refine the curriculum's design. The following questions guided this study: (a) How do learners perceive their motivation and interest towards the Private AI curricular activities? and (b) How do learners engage in collaborative problem-solving during hands-on lab activities?

Methods

We pilot-tested a downsized version of one of the ten Private AI curricular modules, which covered the topics of privacy-preserving machine learning (PPML) and differential privacy (DP). The module was offered in a 2-hour Computer Science (CS) workshop at a public university in the United States. The cohort consisted of 25 participants, with male (68%) and female students (32%), coming from undergraduate (40%) and graduate-level programs (60%). The pilot study employed a parallel mixed-methods design to analyze data gathered from: (a) a post-survey that measured Expectancy Value (Eccles & Wigfield, 2002) and Interest and Choice in Private AI (Roller et al., 2018); (b) semi-structured interviews that prompted students' overall experiences with the curriculum; (c) debriefings, which were recordings of students' post-module reflections on their problem-solving process during hands-on lab activities; and (d) screen recordings that were used to analyze each pair of students' activities during the hands-on lab period.

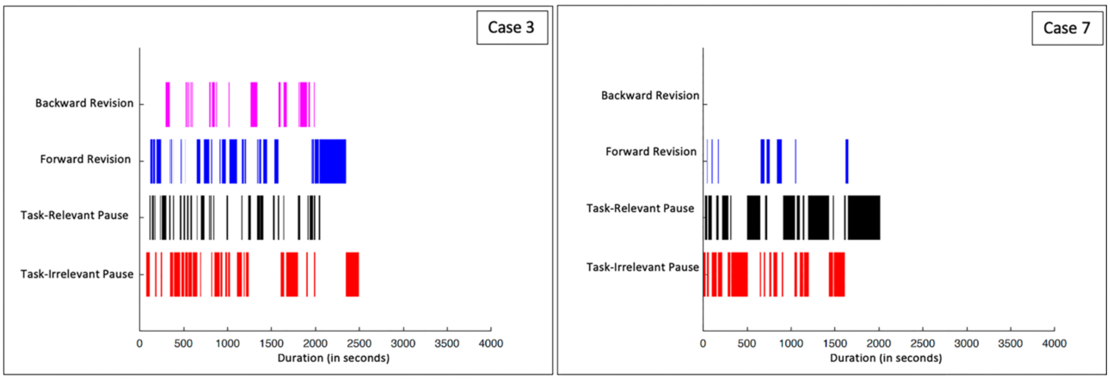
We leveraged a Bayesian *t*-test to test differences in motivation and interest according to learners' gender and education levels, going beyond descriptive statistics, due to the small sample size. To analyze learner experiences with the curricular module, we used the deductive/inductive thematic analysis approach and analyzed data using NVivo software. Regarding learner problem-solving behaviors during the hands-on lab, this paper focuses on Pair 3 and 7, as these pairs represent both a homogeneous (i.e., undergraduate with undergraduate) and a heterogeneous (i.e., undergraduate with graduate) context. The screen recording videos were coded to trace cognitive behaviors associated with pausing and revising (Révész et al., 2019). Additionally, we adhered to Gould's (2014) framework, categorizing data as task-relevant and task-irrelevant. We categorized their revision behaviors as either forward—actions moving from available information toward the goal—or backward—efforts from the goal back to the starting point (Russell, 2020).

Findings and discussion

The survey results indicated that the mean scores ranged from 5.28 for Competence Belief items to 5.60 for Attainment Value/Importance items on the Expectancy Value measure, which utilized a 7-point Likert scale. For the Interest and Choice in Private AI measure, which employed a 5-point Likert scale, scores varied from 3.42 for Outcome Expectations items to 4.48 for Self-Efficacy items. These findings suggest a significant level of motivation, interest, and positive attitudes among students towards the private AI module. The Bayesian independent samples t-tests showed that the BF10 value for the Self-Efficacy component of interest and choice in private AI was greater than 1, demonstrating differences between undergraduate and graduate participants. This indicates that graduate students exhibited higher self-efficacy compared to undergraduates.

The qualitative analysis of the debriefings and interview data closely corroborated the quantitative findings. Students, regardless of their program levels, exhibited positive motivation and interest in the deployed module. When articulating their interest and positive attitudes, students often referenced their abilities and self-assessment of their knowledge. The perceived difficulty, which is closely linked to their confidence in excelling in private AI (i.e., self-efficacy), was notably higher among graduate-level students. For instance, one student stated, "*It's very interesting because… I worked on machine learning research last year, so I basically understand what the speaker is talking about.*"

Figure 1
Pausing and Revision Patterns



Note. The first image is related to Pair 3 (less competent pair), and the second one is related to Pair 7 (more competent pair).

Furthermore, we examined the problem-solving behaviors of two pairs of students (refer to Figure 1). Pair 3 heavily employed a trial-and-error approach, making frequent revisions with brief pauses and relying on external resources such as Google for additional assistance. Despite the tasks having clear algorithmic structures, they attempted to tackle them through heuristic strategies, adjusting their methods based on the outcomes they observed. In contrast, Pair 7 adopted a self-reliant and methodical approach. They engaged in thorough discussions, taking longer pauses to reflect on what they had learned, and selectively employed a forward strategy for problem-solving.

Conclusion

The primary objective of the present study was to pilot test a scaled-down version of one of the newly developed modules, aiming to refine the PCI-centered Private AI curriculum. Overall, participants showed a positive interest in and motivation for the curricular activities. The study revealed a significant difference in self-efficacy between undergraduate and graduate participants. Moreover, the distinct problem-solving behavior patterns highlighted in the case analysis underline the necessity of recognizing learner differences and meeting diverse needs in CS problem-solving, especially concerning coding problems. This study, however, had certain limitations and delimitations, including a relatively small sample size and data collection confined to a single workshop session. Future research should extend to broader contexts (e.g., actual classroom environments) and involve a larger participant pool.

References

Eccles, J. S., & Wigfield, A. (2002). Motivational beliefs, values, and goals. *Annual Review of Psychology*, *53*(1), 109–132.

Gould, A. J. J. (2014). *What makes an interruption disruptive? Understanding the effects of interruption relevance and timing on performance*. [Doctoral dissertation, University College London].

Révész, A., Michel, M., & Lee, M. (2019). Exploring second language writers' pausing and revision behaviors: A mixed-methods study. *Studies in Second Language Acquisition*, *41*(3), 605-631.

Roller, S. A., Lampley, S. A., Dillihunt, M. L., Benfield, M. P., & Turner, M. W. (2018, June). Student attitudes toward STEM: A Revised Instrument of Social Cognitive Career Theory Constructs (Fundamental). In *ASEE Annual Conference & Exposition*. Salt Lake City, Utah.

Russell, S. J. (2020). *Artificial intelligence a modern approach*. Pearson Education, Inc.