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To cite this article:

Haddadian, G., Panzade, P., Takabi, D., & Kim, M. K. (2025). Problem-centered post-secondary computer science education: A study of the private artificial intelligence curriculum. *International Journal of Technology in Education (IJTE), 8*(2), 220-245. https://doi.org/10.46328/ijte.1071

IJTE International Journal of Technology in Education
2025, Vol. 8, No. 2, 220-245 https://doi.org/10.46328/ijte.1071

Problem-Centered Post-Secondary Computer Science Education: A Study of the Private Artificial Intelligence Curriculum

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Article Info

Article History

Received:
15 November 2024
Accepted:
4 March 2025

Keywords

Problem-centered instruction
Computer science education
Private AI
Design research

Abstract

In response to the demand for Artificial Intelligence (AI) experts, this study introduced a curriculum development initiative. The aim was to design and implement a Private AI curriculum to understand the computer science (CS) students' evaluations of the curricular activities and their levels of interest and motivation. Twenty-five students, a mix of undergraduates and graduates, were recruited and a scaled-down version of the curriculum was implemented. A parallel mixed-methods approach was employed. The results reinforced the significance of problem-centered curricula in CS context. Students rated the curricular activities highly and demonstrated strong motivation; however, graduates expressed more favorable view of pairwise collaboration and reported higher self-efficacy. Analysis of coding problem-solving behaviors suggested less competent students often relied on trial-and-error, whereas more competent students employed systematic, forward problem-solving strategies. This study contributes to the field of CS by emphasizing the importance of problem-centered learning to prepare students for real-world AI challenges.

Introduction

Artificial intelligence has brought forth numerous advantages to enhance life. However, AI-based systems have revealed potential harms associated. For instance, individuals share their data with cloud-based AI environments to get recommendations and predictions. However, the methods used by AI systems might produce incorrect outcomes, or the data may include highly sensitive personal details, such as medical history, which could result in infringement upon privacy (Lauter, 2022). AI's potential harms have drawn attention to the trustworthiness of AI. Trustworthy AI is conceptualized as "programs and systems built to solve problems like a human, which bring benefits and convenience to people with no threat or risk of harm" (Liu et al., 2022, p. 5). The dimension of privacy, hereafter Private AI, holds paramount importance because it aims to address privacy concerns such as disclosure of sensitive information by preventing the inadvertent exposure of private information (Alam, 2023). Private AI is conceptualized as the implementation and deployment of AI systems that adopt technical measures, including data anonymization and privacy enhancing technologies such as differential privacy and cryptography to protect sensitive personal data (Alam, 2023).

One effective way to enhance computer science (CS) students' ability to develop Private AI environments is by integrating pedagogical practices with real-world Private AI challenges into the CS curriculum. Given this context, this research aimed to design and develop a curriculum for post-secondary computer science (CS) students, with a focus on Private AI. Problem-Centered Instruction (PCI) was used as the guiding approach. PCI models have garnered significant attention in Science, Technology, Engineering, and Mathematics (STEM) education (Kim et al., 2020) and many stakeholders envision substantial learning outcomes through their integration with CS education (Kwon et al., 2021) as they inherently involve exploring complex and real-world problems (El Sayary et al., 2015). PCI centers instruction around real-life complex problems to enhance learners' knowledge and problem-solving skills, emphasizing the importance of authentic problem-solving activities for creating optimal learning environments (Hmelo-Silver & Barrows, 2015). PCI models prioritize students' individual and collaborative efforts, leveraging complex, authentic, and ill-structured problems to foster active learning, problem-solving, critical thinking, and collaboration. PCI was utilized to deliver a curriculum designed to deepen the understanding of Private AI issues, equipping students to mitigate the negative impacts of AI in real-world scenarios (Li et al., 2023) and to develop trustworthy AI systems.

Despite the value of PCI, there is a paucity of empirical and developmental research on the design, implementation, and evaluation of PCI-based curricula in computer science education, particularly for teaching Private AI. To address this gap, this design research undertook the development of a PCI-based Private AI curriculum with two primary goals. First, we deployed a scaled-down curriculum to evaluate its activities and gather insights for improvement. The study's findings are intended to inform ongoing refinement of the curriculum, instructional strategies, and design principles, ultimately equipping educators to help learners develop fundamental skills for navigating complex Private AI challenges. Additionally, this research demonstrates how PCI principles can inform design considerations and curriculum development practices in computer science education, contributing to the broader goal of adapting AI education to meet evolving requirements.

Literature Review

Private AI Training in CS Education

The number of initiatives dedicated to the design and development of Private AI curricula remains rather sparse. The few initiatives can be categorized in two ways. The first one is in the form of workshops and bootcamps (e.g., Bendechache et al., 2021; Lauter, 2022; Zhang et al., 2020). The workshops were implemented to a) focus on learning and building Private AI applications, b) raise awareness about emerging issues and the challenges posed by AI focusing on trustworthiness, c) explore the techniques to preserve privacy, d) address prominent concerns related to privacy and ethics, and e) provide equitable educational opportunities. The outcomes revealed a positive evaluation of the learning experience and enhancement of motivation to engage with topics of privacy, security, and AI (Bendechache et al., 2021).

The second approach consisted of training modules and educational courses (e.g., Alam, 2023; Fong et al., 2022) to prepare future Private AI experts. Alam (2023) developed a 4-module course on "Safety, Fairness, Privacy, and Ethics of Artificial Intelligence". The course used various pedagogical tools to facilitate learning. These tools included lectures and presentations, case studies, hands-on projects, guest lectures, simulation activities and roleplaying, discussion forums and debates, reading materials, real-world problem-solving activities, and collaborative tasks. Likewise, Fong et al. (2022) presented the results of a 2-year pilot study on the designed and developed standalone training modules that could be incorporated into courses on Private AI. In accordance with the principles of active and experiential learning, twelve learning modules were developed that are freely available to the public.

These efforts, show a growing understanding of the importance of privacy considerations in AI systems. While it is crucial to prioritize both technical knowledge and instructional design methods and theories of learning when designing Private AI courses, no study has been conducted to provide a comprehensive, theory-laden approach to teach Private AI. A study that incorporates established educational theories into the design of courses for delivering a well-rounded educational experience in Private AI is needed. To this aim, it is essential to not only incorporate the required technical knowledge and skills in Private AI but also enhance active learning, collaborative and problem-solving skills in students.

Problem-Centered Instruction (PCI) in CS Education

In higher education, PCI is a recognized instructional approach that aligns with constructivist principles (Hendry et al., 1999). PCI models are diverse (e.g., problem-based learning, project-based learning, case-based learning), and integrating them into the CS curriculum is considered significant (Bosica et al., 2021). Li et al. (2020), for instance, developed a course to teach Natural Language Processing (NLP) with the aim to develop teamwork, critical thinking, communication, and project management skills. Students were required to have weekly presentations and were asked to develop software repositories and algorithms. Student feedback indicated that they could learn better when taking ownership of learning and engaging in active, collaborative problem-solving activities. Furthermore, their course stimulated students' interest and motivation in CS problem-solving. Later, Lee et al. (2021) conducted a case study using PCI-based models in Machine Learning (ML) by doing group projects to promote a self-directed and supportive learning environment, resulting in high student satisfaction. Furthermore, research has demonstrated that effective teamwork is a significant factor in students' motivation and interest (O'Grady et al., 2012).

Moreover, the characteristics of PCI have been identified as the primary driver behind students' increased self-efficacy in CS contexts (Dunlap, 2005). While the importance of PCI and AI education is widely acknowledged, there is a shortage of case studies on PCI applications in CS education, especially in the emerging field of Private AI. Furthermore, PCI-based design principles for CS and AI education need further development, particularly in relation to authentic problems and collaborative problem-solving activities, to enhance students' interest and motivation in curricular activities.

Collaborative Problem-Solving (CPS) in CS Education

Collaboration has been studied in various fields including CS (Wang & Hwang, 2017) and plays an important role in the generation of ideas among CS students (Hopcan et al., 2022) and has its roots in social perspectives of learning and constructivism (Vygotsky, 1978). Engaging in collaborative activities has been shown to improve programming skills, and it helps students critically evaluate various perspectives and solutions while feeling positively engaged through discussion (Faja, 2011).

While collaboration and problem-solving have been studied in CS education (Care et al., 2016; Lin et al., 2014), there remains a need for research focused on specific types of collaboration. For instance, a recent meta-analysis in PCI found that students learn more effectively through constructive interactions within dyads (Kim et al., 2020). Similarly, scholars have highlighted the importance of joint dialogue, where students form dyads and take turns explaining, asking, and answering questions with their partners (Chi & Wylie, 2014). Our literature review reveals a research gap in understanding the dynamics of collaborative problem-solving during pairwise activities in Private AI. CPS for the Private AI curriculum employs pairwise collaboration, and this study focuses on the dynamics within dyads in terms of backward (i.e., starting with solution outlines to achieve desired goals) and forward (i.e., refining the current situation to progress toward goals) problem-solving behaviors (Schunk, 2012).

Research Questions

This design research, aimed at improving the Private AI curriculum and advancing underlying design principles, addresses three key research questions. The first two examine student perceptions, motivations, and interests, while the third delves into an in-depth evaluation of how students interact with the curriculum through observable behaviors.

1. How do participants perceive the quality of PCI-based Private AI curricular activities?
2. How do students perceive their levels of motivation and interest in Private AI curriculum?
3. How do student pairs demonstrate collaborative problem-solving behaviors in hands-on labs?

Private AI Curriculum Development

This project designed a new curriculum that covers a diverse range of private AI topics (Table 1). The overall structure of the curriculum adopted a modular framework that could be arranged in a preferred order, with the completion of the entire curriculum requiring 14 weeks. The course is designed to actively engage learners in a wide array of hands-on labs and class projects to help them apply the concepts and techniques to real-life problems.

The design and development of the curriculum were influenced by a set of design principles rooted in PCI and active learning, along with the incorporation of rapid prototyping methodology (Tripp & Bichelmeyer, 1990) to comprehensively examine the curriculum and refine the design strategies. This allowed us to be able to dynamically develop the content based on evolving experience through iterations (Reiser & Dempsey, 2012). Building on the existing literature (Dostál, 2015; Kim et al., 2020), we incorporated several sequential PCI processes and learning activities into each module. This includes *problem-posing* in which real-life problems are presented in the form of problem scenario (PS). PS is employed to engage learners with real-life situations that have practical relevance to their professional lives (Jones, 2006).

Table 1. The Private AI Curriculum Outline

Module	Topic	Weeks
1	Introduction to Private AI	1.0
2	PPML[1] with Differential Privacy	1.5
3	PPML with Fully Homomorphic Encryption	1.5
4	PPML with Secure Multiparty Computation	1.5
5	PPML with Trusted Execution Environment	1.5
6	Privacy-preserving Distributed Machine Learning	1.5
7	Privacy Attacks on Machine Learning Data	1.5
8	Privacy Attacks on Machine Learning Models	1.5
9	Privacy-preserving Generative Adversarial Networks	1.0
10	Private Deep Reinforcement Learning	1.5
Total		14

Note. [1] Privacy-preserving Machine Learning

In *instructor-led instruction*, students acquire content knowledge through instruction while making connections between their acquired knowledge and the authentic problem scenario posed at the beginning of the class. The effect of PCI is augmented when it is offered with appropriate scaffolding strategies by instructors (Kim & Kim, 2020). In line with this idea, the curriculum was designed to let the instructor incorporate worked examples (WE) as a scaffolding strategy. WEs provide a step-by-step guide to solving the problem at hand and act as an effective approach for enhancing problem-solving among learners. By utilizing WEs, learners are encouraged to study and extract knowledge on how to apply the demonstrated problem-solving strategies to similar problems in learning programming (Margulieux et al., 2020).

In *exploration and integration*, students expand upon their initial understanding of the problems by doing experiments and analyzing them in hands-on labs to evaluate the practicality of concepts and ideas. Hands-on labs as a learning activity allow students to actively engage with and utilize what they have learned (Alam, 2023). Students have the chance to engage with the concepts and techniques through tangible resources on computers. They experiment with their hypothetical solutions, apply their theoretical concepts, gain practical experience, adjust, and manipulate available resources to learn and find proper solutions.

In *articulation and resolution*, students engage in reflective thinking focusing on their problem-solving process. Student pairs modify their solutions if required and showcase their solutions to the class, receiving feedback and critique. Each module of the curriculum has been designed following sequential PCI-based learning activities. In the current study, an individual module was scaled-down to address the intended research questions. The curriculum was designed with an emphasis on prioritizing paired collaboration. Through joint dialogues, where students are paired in dyads, they actively participate in a reciprocal exchange of ideas and constructive conversation in a collaborative learning environment to solve the problem (Chi & Wylie, 2014). Reflection activities, done in pairs, act as peer-mediated guidance which helps learners engage in a meaningful understanding of the content knowledge, and enable them to learn from each other.

Methods

Research Design

This study employed a parallel mixed-methods design (Tashakkori et al., 2020) to ensure research rigor (Denzin, 2017). The design consisted of two strands: one focused on collecting and analyzing quantitative data (surveys), while the other focused on qualitative data (interviews, debriefings, and screen recordings). Table 2 summarizes the data sources.

Table 2. Summary of Research Questions and Related Data Sources

Research Question	Type	Data Source
Research question 1	Mixed-method	Survey, Interview, Debriefing
Research question 2	Mixed-method	Survey, Interview, Debriefing
Research question 3	Qualitative	Interview, Debriefing, Screen recording

Participants

Twenty-five students majoring in CS and computer information systems (CIS) were recruited from a postsecondary university degree program with individuals being at different stages of their educational and professional journeys (see Table 3).

Table 3. Participants' Information and Data Sources

Group #	ID	Gender	Ethnicity	Degree	Data Sources		
					Prior Knowledge test	Debriefing	Interview
1	S1	Male	Asian	Graduate	Yes**	No	No
	S2	Male	Asian	Graduate		No	No
2	S3	Female	Asian	Graduate		No	No
	S4	Female	Other	Graduate		No	No
3*	S5	Male	Asian	Undergraduate		No	Yes
	S6	Male	Other	Undergraduate		No	No
4	S7	Male	Prefer not to say	Graduate		No	No
	S8	Male	Asian	Graduate		No	No
5	S9	Female	Asian	Undergraduate		Yes	No
	S10	Male	Asian	Graduate		No	No
6	S11	Male	Black/African American	Undergraduate		Yes	No
	S12	Male	Black/African American	Undergraduate		No	Yes
7*	S13	Male	Asian	Undergraduate		No	No

					Data Sources		
Group #	ID	Gender	Ethnicity	Degree	Prior Knowledge test	Debriefing	Interview
	S14	Female	Asian	Graduate		Yes	Yes
8	S15	Male	Black/African American	Undergraduate		No	No
	S16	Male	Asian	Undergraduate		No	No
9	S17	Male	Asian	Graduate		No	No
	S18	Male	Asian	Graduate		No	No
N/A	S19	Female	Asian	Undergraduate		No	No
N/A	S20	Male	Asian	Graduate		No	No
N/A	S21	Male	Black/African American	Undergraduate		No	No
N/A	S22	Female	Asian	Graduate		No	No
N/A	S23	Female	Asian	Graduate		No	No
N/A	S24	Female	Black/African American	Graduate		No	No
N/A	S25	Male	Black/African American	Graduate		No	Yes

Note. *Pairs shown in asterisk were selected for the pairwise collaborative case study. ** All participants.

While prior knowledge of Private AI was desirable, it was not a prerequisite for participation. For research questions one and two, we analyzed data from all participants. Participants voluntarily chose to participate in debriefing and interview sessions (i.e., three students in debriefing and four students in interview). However, since seven out of 25 participants did not engage in the pair work, we excluded their data from analysis for research question three. The instructor was a 28-year-old female Ph.D. candidate having four years of experience in the field, doing research and teaching in Private AI, data mining, and machine learning through classrooms and hands-on labs.

Within this population, two pairs were selected to address the third research question for the pairwise collaborative case study, specifically pairs 3 and 7 (indicated by asterisks in Table 3). Pair 3 is considered less competent due to their status as undergraduates (both juniors), while Pair 7 is considered more competent and knowledgeable because it includes a graduate student with over three years of related work expertise.

Overview of the Scaled-down Module

As a part of the rapid prototyping, this study downscaled Module two to focus on fundamental concepts, providing early, focused feedback to observe students and get insights for refining future iterations. Consequently, a 2-hour in-person session was offered during the summer semester of 2022 at a public university in the southeastern region of the United States. The study was designed for graduate students as well as individuals with an interest in learning about Privacy-Preserving Machine Learning (PPML), including undergraduates. The learning objectives of this session were to provide students with an understanding of PPML using Differential Privacy (DP). DP is a technique used to protect the privacy of individuals while enabling the analysis of data.

Instruments

Prior Knowledge Test

A 5-item, paper-and-pencil knowledge test was initially created by the subject matter expert (a Ph.D. level curriculum developer) to explore the students' initial understanding of the Private AI concepts. Then, the test items were reviewed for validity by a Private AI expert (a CS faculty member). Face validity is a standard practice in the development of psychological and educational assessments (Beck, 2020). The Private AI expert meticulously evaluated the developed items to ensure they effectively captured students' prior knowledge. The questions were a mixture of multiple choice and fill in the blanks. The items were scored on a scale from 0 to 20, with each item worth 4 points. For fill-in-the-blank items, no partial credit was awarded for incomplete responses.

Quality of Curricular Activities Survey

This instrument was specifically designed to evaluate learners' perceptions of the quality of the curricular activities (see Table 4). The initial survey contained items related to problem scenario. However, due to the instructor's inability to provide the scenario in depth as initially planned, participants only gained a superficial understanding of the overarching problem. As a result, we opted to exclude the questions related to the "problem scenario". We then developed a 20-item survey utilizing a 5-point Likert scale, ranging from 1 (strongly disagree) to 5 (strongly agree).

Table 4. Quality of Curricular Activities Survey Components, Definitions, and Examples

Components	Item N	Cronbach's Alpha	Definition	Example Item
Instructional Module	8	0.934	The items ask about the suitability of the learning resources, clarity of module expectations, and logical organization of the content.	The instructional module expectations (aims, content) were clarified for me at the beginning of the module.
Instructional Lecture	3	0.927	The items ask about the relevance of the lectures, its content organization, and its effectiveness.	The lectures were relevant to the topics and effective.
Hands-on Lab	5	0.872	The items aim to evaluate the success of the hands-on labs in providing a practical learning experience.	The tools and resources for the hands-on labs were easy to use.
Pairwise	4	0.935	The items gather feedback on	Collaboration with

Components	Item N	Cronbach's Alpha	Definition	Example Item
Collaboration			pairwise collaboration, by evaluating participants' experiences of working in pairs.	peers helped me engage in problem-solving.

Expectancy Value Survey

This study assumed that an improved learner experience, augmented by the deployment of the PCI model, leads to positive learner motivation and interest in Private AI. Therefore, we developed a motivation survey suiting out specific context according to the key components of expectancy-value theory (Eccles & Wigfield, 2002) that have been extensively covered in the literature (Hylton et al., 2021). Eccles and Wigfield (2002) considered "expectancies refer to beliefs about how one will do on different tasks or activities, and values have to do with incentives or reasons for doing the activity" (p. 110). The research team including subject matter experts underwent multiple modification processes to ensure that every question fits with the context. The questionnaire utilized a 7-point Likert scale (see Table 5), ranging from 1 (minimum intensity) to 7 (maximum intensity).

Table 5. Expectancy Value Survey Components, Definitions, and Example Items

Components	Item N	Cronbach's Alpha	Definition	Example Item
Task Value	5	0.935	A subjective importance or personal motivation that an individual assigns to a particular task.	Is the amount of effort it will take to do well in Private AI worthwhile to you?
Attainment Value/ Importance	2	0.868	The significance of performing effectively in a specific task.	I feel that, to me, being good at solving problems that involve Private AI techniques is…
Expectancies for Success	3	0.787	Individual's expected performance on upcoming tasks, which can be either in the short-term or long-term future.	Compared to other students, how well do you expect to do in Private AI modules?
Competence Beliefs	2	0.874	How capable an individual perceives themselves to be in performing a task.	If you were to order all the students in your Private AI class from the worst to the best, where would you put yourself?

Components	Item N	Cronbach's Alpha	Definition	Example Item
Perceived task difficulty	7	0.915	Individual's perception of how hard or challenging a task is to complete.	How hard would you have to try to do well in the Private AI course?

Interest and Choice in Private AI Survey

The items for this instrument were created by modifying items from Roller et al.'s (2020) validated (SIC-STEM) Survey instrument for assessment of Social Cognitive Career Theory Constructs (SCCT). The original survey intended to assess the various aspects of SCCT that influence students' choices to either pursue or not pursue a career in STEM fields. Accordingly, we modified items to adapt to learner interest in Private AI context. We purposefully incorporated all the elements of the original survey related to engineering and technology. This includes self-efficacy, outcome expectations, interests, and choice actions, except for choice goals as it did not align well with our specific context.

The resulting questionnaire consisted of 12 items using a 5-point Likert-scale, with responses ranging from 1 (strongly disagree) to 5 (strongly agree). Our initial review showed low reliability for two components: Interest and choice actions. This could potentially be attributed to including reverse items in our metrics. To ensure the accuracy of our conclusions, we further examined individual item reliability statistics. Omitting item 2 for interest increased the reliability value to 0.732, while no potential improvement was found in the items of choice actions. Consequently, we continued with the remaining interest items but dropped all the choice action items for data analysis (see Table 6).

Table 6. Interest and Choice Survey Components, Definitions, and Example Items

Components	Item N	Cronbach's Alpha	Definition	Example Item
Interest	2	0.732	The items assess whether students have a positive or negative attitude.	I am curious about how Private AI techniques work for AI/ML.
Self-Efficacy	3	0.761	The items are centered on one's perceived ability and reflect an individual's judgment of their competence.	I believe I can be successful in using AI/ML empowered by Private AI techniques.

Components	Item N	Cronbach's Alpha	Definition	Example Item
Choice Actions	3	Omitted	The items are centered around a goal to do something in a related activity.	The skills I learn while solving problems in Private AI will help me in my future job.
Outcome Expectations	3	0.639	The items are structured around a cause-and-effect relationship, wherein the cause represents the decision or action made by the individual, and the effect shows the consequences.	If I learn Private AI, then I can improve the privacy of AI and machine learning systems.

Semi-Structured Interviews

Semi-structured interviews were used with questions investigating students' experience with hands-on labs (e.g., How do you evaluate the hands-on labs?), their overall experience with the instructional module (e.g., How do you describe the quality of content?), and training outcomes (Do you have any suggestions that would help to improve the modules?). The instructor's semi-structured interview intended to solicit the instructor's teaching experience (e.g., Describe your approach to deploying the curriculum in your class?), experience with hands-on-labs (e.g., Can you describe the difficulties/barriers when teaching the module using hands-on lab?), and the overall experience with the instructional module (e.g., What did you like most about your teaching experience using instructional modules?)

Procedure

Students were initially introduced to the session and the aim of the study and then completed an electronic consent form approved by the Institutional Review Board (IRB). Subsequently, they were asked to complete a prior knowledge test to evaluate their level of familiarity with the content. Students recorded their screens using the Webex platform or their system's default recorder as soon as they started working on the hands-on activity in pairs. At the end, students completed three surveys. Additionally, three students voluntarily participated in an in-class debriefing session. Following this, volunteers were invited to share their thoughts through interview. Four students participated in online interview, which were recorded and transcribed.

Data Analysis

To address the first two research questions, this study analyzed questionnaire responses using descriptive statistics, including mean, standard deviation, and variance. Additionally, Bayesian t-tests were conducted to examine whether the perceived quality of curricular activities differed between undergraduate and graduate-level students, with the aim of identifying specific areas where the curriculum might require adjustments. This test was suitable given our small sample size and enabled us to differentiate between graduate and undergraduate students. Understanding these differences could help us evaluate how the curriculum performs across different academic levels and refine it to better meet the unique needs of each group. The interpretations were conducted following Jeffreys's (1961) Bayes factor scale of evidence.

The qualitative data was transcribed, and two researchers conducted several iterative and reflexive readings of the transcripts, ensuring credibility and rigor (Tobin & Begley, 2004). The researchers simultaneously took notes to facilitate the integration of preliminary analysis and interpretations. This was achieved through a dual deductive/inductive thematic analysis model (Bingham & Witkowsky, 2022). We drew themes from previous empirical literature related to learners' perceptions and attitudes regarding PCI models—deductive approach (Jaganathan et al., 2020). These initial themes were combined with new themes that emerged from an iterative process of repeated readings and reviews—inductive approach, resulting in four categories (see Table 7).

We selected two pairs' screen recordings which were the most comprehensive with fewest interruptions, covering a significant portion of the lab session to provide an enriched data. Reviewing these cases enabled us to examine peer dynamics within homogeneous (undergraduate-undergraduate) and heterogeneous (undergraduate-graduate) group compositions, providing a more comprehensive understanding of the complexities involved.

Table 7. The Coding Scheme for the Qualitative Data

Parent code	Child code
For Interview and Debriefing Data	
Knowledge and application	Practical application of the attained knowledge (3)
	Prior knowledge and experience (8)
Learning-related aspects	Promoting learners' involvement, motivation, and interest (25)
	Communication and interaction skills (3)
	Self-directed learning (2)
	Learners' learning preferences and personal attributes (4)
Instructor-related aspects	Teacher's role and presence (12)
Instructional and Implementation Challenges	Time requirements and constraints (9)
	Logistical affordances (2)
For the Screen Recordings (Video Data)	
Pause	Task-relevant (60):
	Students engage in a process of searching for solutions online, communicating with peers/teacher, evaluating code output, and identifying errors/bugs.
	Task-irrelevant (51):
	System runtime (the execution phase of a computer program that is dependent

Parent code	Child code
	on the computers' operating system and hardware) and distractions like system notifications or unrelated conversations.
Revision	Backward (19): The problem solvers start with the goal of either resolving the program errors/bugs or enhancing the performance and efficiency of the code. Then, they determine the specific subgoals that are necessary to achieve it. They gradually identify the requirements for each subgoal, progressing toward the initial state of the program (Schunk, 2012). Forward (39): It involves a process of making multiple iterative changes from the initial state or current situation to gradually move closer to the desired goal of fixing program errors/bugs or enhancing the performance and efficiency of the code, often requiring multiple adjustments along the way (Schunk, 2012).

Note. The number within parentheses indicates the count of observed instances.

The videos were coded for pause and revision behaviors using NVivo 14, focusing on pausing patterns to link them to cognitive processes (Kumpulainen, 2015). Gould (2014) introduced pauses as being task-relevant and task-irrelevant. The former is deliberate moments of pausing during programming to engage in activities that are directly associated with the task at hand. For example, more frequent pauses correspond to increased cognitive activity (Kumpulainen, 2015) and longer pauses are indicative of greater mental effort (Damian & Stadthagen-Gonzalez, 2009). The latter, by contrast, refers to irrelevant pauses or delays that serve no productive purpose to solve the problem. Regarding revision behavior, learners must use reasoning strategies to modify their responses. In deductive problem-solving domains such as logic and probability, this occurs through employing either forward or backward reasoning strategies. Forward reasoning starts with available information and moves toward the goal, while backward reasoning begins with the goal and works backward to identify the starting point or given state (Abdelshiheed et al., 2022). In this research, revision refers to the process of modifying the program, either forward or backward. Both processes occur with two purposes, either error correction (identifying and fixing errors, bugs, or issues) or optimization (improving the program for better efficiency).

Results

RQ1

Overall, students perceived the curricular activities as high-quality. The aggregate mean scores ranged from 4.52 for the *instructional module* to 4.570 for the *pairwise collaboration* (Table 8). The Bayesian independent samples *t*-test showed that in *pairwise collaboration*, a BF_{10} value greater than 1 favors the alternative hypothesis, indicating evidence for differences between undergraduate and graduate students (Jeffrey, 1961). The data exhibited 1.250 times higher likelihood under the alternative hypothesis (H_1) in comparison to the null hypothesis (H_0).

Table 8. Descriptive Statistics and Bayesian Independent Samples T-Test for the Quality of Curricular Activities

	Groups	Subgroups	Descriptive Statistics			Bayesian Independent Samples *T*-Test	
			n	Mean	SD	BF_{10}	error %
Instructional Module	Total		25	4.45	0.56		
	Education	Undergraduate	10	4.28	0.71	0.86	0.003
		Graduate	15	4.62	0.41		
Instructional Lecture	Total		25	4.49	0.605		
	Education	Undergraduate	10	4.33	0.66	0.73	0.003
		Graduate	15	4.66	0.55		
Pairwise Collaboration	Total		25	4.53	0.49		
	Education	Undergraduate	10	4.35	0.61	1.25*	0.004
		Graduate	15	4.71	0.37		
Hands-on Lab	Total		25	4.49	0.58		
	Education	Undergraduate	10	4.30	0.77	0.95	0.003
		Graduate	15	4.68	0.39		

The qualitative analysis on the debriefing and interview data showed that in evaluating their overall experience with the *instructional module*, students expressed satisfaction and interest, noting their enjoyment of the module by saying, *"No suggestions truly speaking because I think if we only have more sessions, then, it will be more interesting because I really enjoyed, and it was a good experience."* Students particularly noted that the *instructional module* facilitated independent learning and encouraged them to further explore the topics outside the classroom. For instance, one student stated, *"I went in kind of like a solo person, not knowing what to expect, and I left out making new friends, learning materials, and actually went home and kind of researched it [the learned concepts] a little further….I think you guys did an awesome job."* One student reflected on the instructional module's effectiveness in facilitating their learning experience, tailoring to their individual learning preferences by saying, "*I'm a person…that has more of a tactile learning style, so …, it [the module] helped me learn it better."*

In assessing the *instructional lecture*, students highlighted the contributing role of the instructor in their learning experience. Students reported being more engaged when instructor was actively engaging to facilitate learning. This is evidenced by one student saying, "*I was more focused on what instructor was talking [than the learning slides]…"*, or they appreciated instructors' approach to provide help and scaffolding. For instance, *"…my learning experience was good, and I think the instructor who went around and assisted people that didn't really have some practical knowledge, it was good."* As a part of the instructional lecture content, students also referred to the WE and appreciated its inclusion by saying, *"very simplified explanation [referring to the WE] for someone like me, and I think it was very simplified for the beginners."*

In terms of *pairwise collaboration*, students' comments reflected their higher level of engagement towards collaborative learning, for instance by taking a proactive approach to collaboration. For example, one student mentioned, *"I want to collaborate with the others. So, I taught my teammate in the session, how to get to the model and how to build it, and I very enjoyed it."* While expressing the opinion about *pairwise collaboration*, the same student recalled his positive prior experience with *hands-on labs* done in pairs, and expressed confidence in his abilities, attributed it to his prior experience by saying, *"the hands-on lab, I felt like it was fine with me, and it will be fine with me because I've been pretty good at physics [hands-on], and I'm confident with that, and I enjoyed it."* The instructor highlighted the pairwise activities to be efficient by saying, "*having the worked example…and having the teams,… I think that was very, very time efficient and very effective because if we were to do the same thing one-on-one like have each student work on their own, they would have not learned much."*

More specifically, students shared their experience with the *hands-on lab.* One student remarked, *"…the hands-on lab was quite good because initially, I was thinking that many computer science students find it difficult to carry out…but then, fortunately, when I got to the study, I noticed that some codes were actually given for people that don't really have knowledge about coding to grab. So, the hands-on lab was good and interesting."* Students also highlighted the significant role of activities in *hands-on lab* to help them learn how to apply the concepts in real-world settings. For instance, one student mentioned *"I think it was an awesome lab as I was able to not only learn about Private AI, but I was also able to get in and see how it is in real life like, the technical side of things."*

However, during our analysis, some ideas emerged as students frequently highlighted challenges, suggesting the need for adjustments in curriculum design. A student expressed, "*I think I can catch up with it [the concepts in hands-on lab], but I don't know I understand it more deeply than I expected, and more importantly, for someone who doesn't have a prior experience like me, it can be more difficult to understand… ."* This comment underscores the role of existing knowledge and experience in fully grasping the content, pointing out that the module in general, and the hands-on lab in specific, could be challenging for those without prior experience, thereby emphasizing the importance of considering this component in further Private AI curriculum designs. Despite the importance, the limited time available made it challenging to comprehensively grasp deeper concepts, even for those with the existing knowledge and experience. One student with a data science background noted, *"Even though I have a data science background, but for me to understand in half an hour, or one hour duration was a little difficult. ..., it took me a little while and I did not go in depth… ."* These emerging ideas suggest that curriculum design adjustments are fundamental at this stage.

Such challenges were consistently acknowledged by the instructor, who noted that delivering this workshop was highly demanding. Teaching the module in such a short session was "*an extremely challenging task…as it was a lot of content to teach effectively…the students, definitely, found a lot of information to deal with… ."* and recommended having *"less content in each session and more hands-on practice".* She further noted that a significant portion of hands-on lab time consumed by troubleshooting which could be mitigated *"if a lot of [such] information is given much beforehand."* Ensuring that all challenging aspects are thoroughly addressed will prevent such barriers from hindering the learning process.

RQ2

The assessment of students' motivation and interest involved the analysis of two surveys: 1) the Expectancy-value survey which indicated the aggregate mean scores ranged from 5.28 for the *competence belief* to 5.60 for the *attainment value/Importance*, and 2) the Interest and Choice in Private AI survey that demonstrated an aggregate mean ranging from 3.42 for *outcome expectations* to 4.48 for *self-efficacy* (Table 9). The results revealed that students had a relatively strong motivation to engage in AI tasks and exhibited interest and positive attitudes towards the AI course. However, their *outcome expectations* were relatively low (M = 3.427) compared with other components, suggesting that participants may not see the benefits of mastering the new topic.

Table 9. Expectancy-Value and Interest and Choice in Private AI Surveys

Categories	Descriptive Statistics		
	Mean	SD	Variance
Expectancy-Value			
Task Value	5.552	1.382	1.937
Attainment Value/ Importance	5.600	1.382	1.910
Expectancies for Success	5.387	1.216	1.581
Competence Belief	5.280	1.428	2.044
Perceived task difficulty	5.366	1.366	1.881
Total	5.437	1.354	1.870
Interest and Choice in Private AI			
Interest	4.280	0.753	0.583
Self-Efficacy	4.480	0.618	0.384
Outcome Expectations	3.427	1.260	1.746
Total	4.062	0.877	0.904

The BF_{10} values obtained from the independent samples *t*-test for the Expectancy-value and the Interest and Choice survey were less than 1, indicating a weak difference in terms of education level across most categories (see Table 10). However, in *self-efficacy*, the BF_{10} greater than 1 favors the alternative hypothesis indicating evidence for differences between undergraduate and graduate students. The data is 1.267 times more likely under the alternative hypothesis (H_1) than the null hypothesis (H_0) for *self-efficacy*.

Table 10. Descriptive Statistics and Bayesian Independent Samples T-Test for the Interest and Choice Survey

	Groups	Subgroups	Descriptive Statistics			Bayesian Independent Samples *T*-Test	
			n	Mean	SD	BF_{10}	error %
Interest	Total		25	3.97	0.38		
	Education	Undergraduate	10	4.050	0.296	0.529	0.002
		Graduate	15	3.889	0.458		

	Groups	Subgroups	Descriptive Statistics			Bayesian Independent Samples *T*-Test	
			n	Mean	SD	BF_{10}	error %
Self-Efficacy	Total		25	4.45	0.50		
	Education	Undergraduate	10	4.260	0.624	1.267*	0.004
		Graduate	15	4.633	0.379		
Outcome Expectations	Total		25	3.45	0.99		
	Education	Undergraduate	10	3.567	0.876	0.418	0.002
		Graduate	15	3.333	1.107		

Generally, students showed strong motivation and interest. They referred to their ability and their judgment of their knowledge. They often referred to their competence beliefs, attaching it to their understanding and enjoyment. One student, for instance, stated *"My research is actually into kind of security and privacy. So, I was able to follow along with what was being taught*", and *"I think it's more enjoyable for someone who have experience."* On the contrary, some students who initially felt less confident in their prior knowledge perceived the task as challenging. For instance, one student pointed to his lack of prior experience in Private AI and considered it to be difficult to grasp, as exemplified by the quote, *"for someone who doesn't have a prior experience like me can be more difficult to understand."* In summary, students generally hold positive beliefs, while some students initially struggled with addressing the topic and tasks, which provides insight into areas for further improvement in curriculum design, particularly for those who are less confident and new to the subject.

RQ3

Students' pausing and revision behaviors (see Figure 1) as well as their forward and backward reasoning (see Figure 2) are visually mapped. Pair 3 comprised two undergraduate male students (and is referred to as the less competent pair due to their limited experience with Private AI. Conversely, Pair 7 consisted of one undergraduate male student and one graduate female student, is considered the more competent pair.

Pair 3 approached the tasks with a non-systematic, trial-and-error mindset (repetitive revisions with short pauses). They tried to find a solution to each subtask once at a time. For instance, during Task 1, they engaged in frequent and iterative interactions between the collaborative notebook and external Google resources. They copied the codes from Google, then tested and modified them accordingly to complete the task. Then, they moved on to the next individual subtask. These series of trials and tests were performed with short intervals—mostly unrelated pauses. In Task 2, the pair displayed a similar pattern of trial-and-error iterations. However, in Task 3, they adopted a different approach with relatively longer pauses to discuss and find the necessary information, followed by running a series of optimized codes with no errors.

In contrast, Pair 7 did not rely on external resources, such as Google search, nor did they take a trial-and-error process. They adopted a self-reliant approach, often pausing for extended periods to grasp and exchange ideas, followed by subsequent revisions as necessary to ensure successful task completion and understanding. Their thoughtful and deliberate approach toward solving the problem was indicated by Luna, *"...I am somebody who likes to study everything in depth. So, for me, the code, understanding the code, that took me a while."* Notably, when they encountered an error, their strategy involved referring to the worked example, reviewing the task requirements, engaging in collaborative discussions with their peer, and seeking guidance from the instructor.

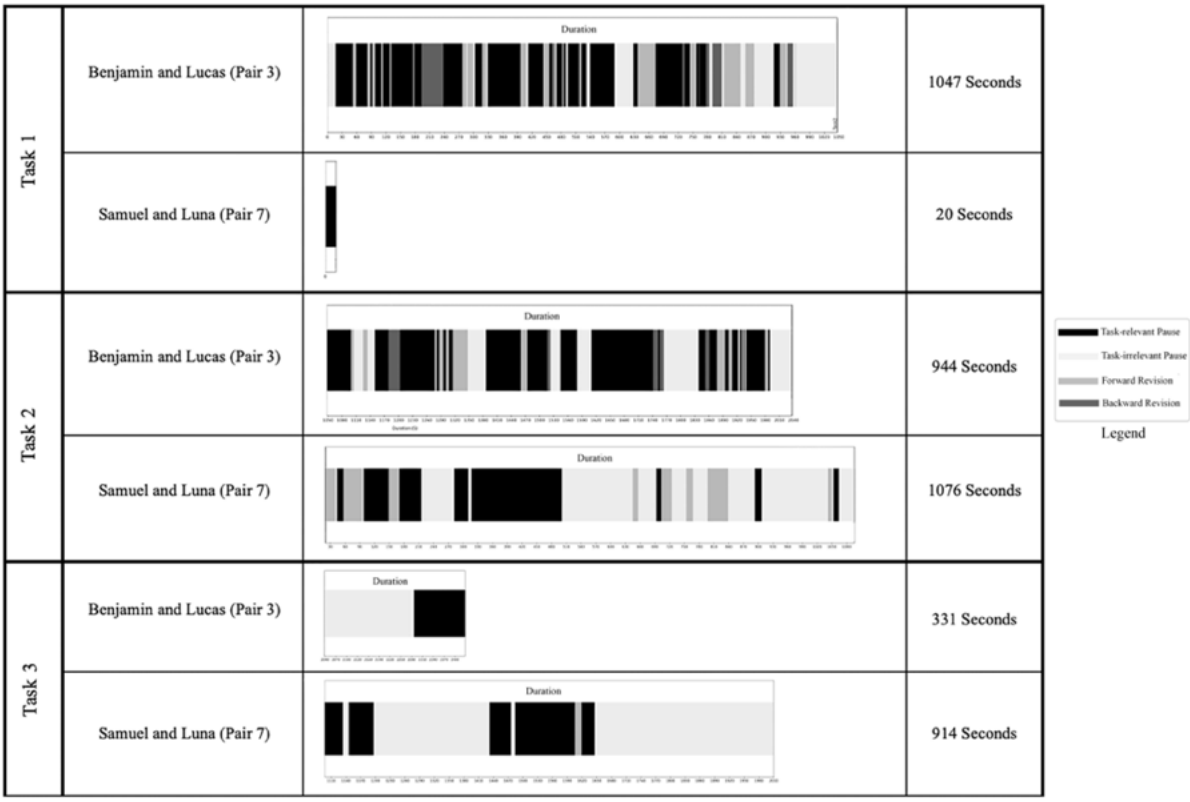

Figure 1. Pause and Revision Patterns

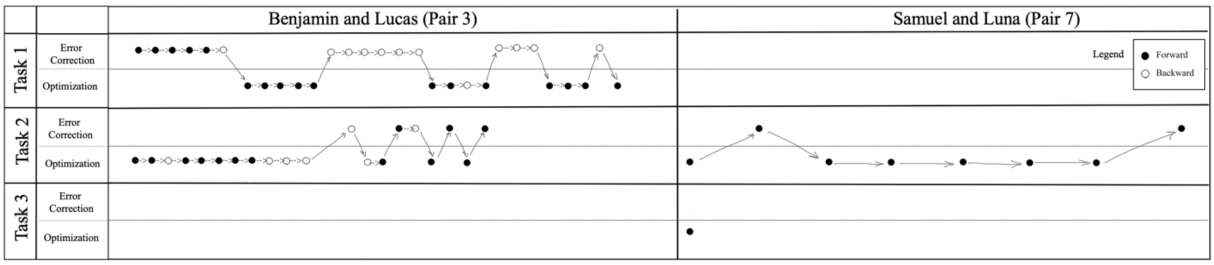

Figure 2. Backward and Forward Revisions

Pair 3 used a mixture of frequent forward and backward approaches to either optimize their code or make error corrections throughout the tasks. Mainly, however, they started with available information they had and moved toward the ultimate goal (i.e., forward approach) and explored the necessary steps to achieve the expected outcome. This was done along with frequent trial-and-error patterns. Compared to Pair 3, Pair 7 completed tasks 1 and 3 without significant revision effort, and their problem-solving approach primarily revolved around selectively utilizing the forward strategy. When faced with errors, they consistently revisited the initial sections of their code, reviewing all the dependencies from the beginning to investigate the problem and perform error correction effectively. The students in this pair seemed to have a more in-depth understanding of the hands-on assignments and were thereby able to formulate an appropriate plan to solve the tasks. More information on student behavior (i.e., pausing and revision patterns) can be found in Haddadian et al. (2023; 2024).

Discussion

Design Considerations from RQ1: Training for Essential Collaboration Skills Alongside Content

The participants evaluated the curricular activities in Private AI context as high. Despite lack of Private AI context in the literature adopting a PCI approach, our findings resonate the literature highlighting the potentials of PCI curricular activities in enhancing critical thinking skills, active learning, and problem solving by involving students in authentic, rich problem-solving environments (Hmelo-Silver & Barrows, 2015; Kim et al., 2020). The positive perceptions of students could be the consequence of the features of PCI and its appropriateness for Private AI context, including active learning, and problem-solving activities.

There was an absence of a significant difference between graduate and undergraduate students, in terms of their perceptions of the quality of curricular activities. In addition, in our study, graduate students perceived a slightly higher level of quality regarding pairwise collaboration (BF_{10} = 1.250) than undergraduate students. Although literature in PCI emphasizes that most learners hold positive perceptions regarding collaboration (Tan, 2021), this observed difference align with Tan’s (2021) assertion that more knowledgeable students, like graduates, view collaboration more favorably. Nevertheless, to ensure effective implementation of PCI approaches in Private AI, preparing some materials, particularly prior to PCI implementation (Tan, 2021), to familiarize learners with requisite collaboration skills is fundamental (Woods, 2000). Although graduate students rated slightly higher, this does not diminish the substantial advantages undergraduates experienced, particularly when paired with more experienced individuals and furnished with suitable scaffolding and timely support. Given the emphasized role of teachers as scaffolds (Belland et al., 2008), it may be plausible to consider that graduates and more knowledgeable peers, in this case, acted very effectively as scaffolds, thereby facilitating learning (Hmelo-Silver, 2019; Walker & Leary, 2009).

Design Considerations from RQ2: Continuous Formative Support for Building Efficacy

Students exhibited relatively strong motivation and interest in the PCI-based curriculum in Private AI. These results may be attributed to both the potential of PCI to enhance learners’ involvement, motivation, and interest (Dube et al., 2014; Jaganathan et al., 2020; Tseng et al., 2008) and the participants’ inherent motivation, as they volunteered for the training workshop. We observed a lower level of outcome expectations compared to other components. This finding suggests that short-term exposure to a scaled-down module was insufficient for students to recognize the potential benefits of the tasks. It underscores the need for more substantial training with multiple modules to foster higher outcome expectations, ultimately leading to increased interest.

We identified a need for motivational support to maintain or enhance students’ self-efficacy. Results from

Bayesian analysis revealed significant differences in self-efficacy among students. For example, undergraduate students may experience lower self-efficacy due to limited experience and exposure to various academic challenges, whereas graduate students have typically navigated foundational courses and the demands of rigorous graduate-level coursework. Similar discrepancies in self-efficacy levels may also exist among students with varying competency levels within the same grade.

Embedding ongoing and prompt formative support mechanisms into the curriculum could address these disparities. Students frequently reflected on their abilities and competence when integrating new information, underscoring how self-perceived competence and ability influence their overall learning experience. This highlights the critical role of perceived competence and self-efficacy in creating a rich educational experience (Gijselaers, 1995).

Design Considerations from RQ3: Pairing Learners for Collaboration Based on Competence Levels

The saying, 'the rich become richer, while the poor become poorer,' was evident in performance differences among paired learners (Anderson, 1990, 1993; Bruning et al., 2004). Despite the well-defined and algorithmic nature of the tasks, the less competent pair strove to solve the problems through a heuristic, non-systematic approach, adapting their strategies based on the observed results. They relied heavily on exploring external resources and doing random trial-and-errors using a combination of forward and backward reasoning strategies to accomplish the tasks based on random patterns (Feltovich et al., 2006; Mayer, 1992; Van Der Linden et al., 2001).

In contrast, the more competent pair, however, showed more systematic reasoning and problem-solving skills and seemed to have used established patterns in their mind to solve the problem-solving task more effectively (Feltovich et al., 2006; Van Der Linden et al., 2001). They accomplished the task more effectively and in a shorter time showcasing the efficiency of expert reasoning skills in contrast to the less competent pair (Feltovich et al., 2006; Horn, J., & Masunaga, 2006). They employed selective forward problem-solving strategies when considered most useful (Feltovich et al., 2006; Schunk, 2012). They started by recognizing the problem, breaking it down into parts, generating a proper approach for solving it, and then solving the problem parts in sequence (Bruning et al., 2004; Mayer, 1992).

Although analyzing only two pairs restricts our ability to draw generalizable conclusions, it still provides valuable preliminary insights into student behavior patterns. These findings underscore the practical and theoretical importance of recognizing and accommodating diverse problem-solving styles, peer dynamics, and skill levels (Steier & Mitchell, 1996). To achieve this, it is essential to gather learner information through formative assessments and use these insights to pair learners effectively for collaborative problem-solving. For example, intentional heterogeneous grouping by an instructor can provide each pair with a more knowledgeable peer who can scaffold deeper engagement, model effective problem-solving approaches, and stimulate reflective practices, enhancing the overall learning experience (Cetin et al., 2014). Expanding the number of cases in future studies would enhance the reliability and depth of the findings.

These grouping strategies may be more effective when combined with instruction in problem-solving strategies as part of the curriculum (Fülöp, 2021). While trial-and-error is a basic method of knowledge acquisition, it often emphasizes finding a solution over understanding the underlying principles (Montgomery, 2017). Research has shown that this approach can reduce learning outcomes (Van Der Linden et al., 2001). Teaching problem-solving strategies can help students adopt either a balanced or more structured approach to problem-solving, ultimately enhancing their learning experience.

Limitations

The limited number of participants and the narrow focus of the study could affect the generalizability of our findings. This implies to proceed with caution when generalizing the outcomes to other settings. Within the Interest and Choice in Private AI survey, it was observed that certain components demonstrated unacceptable reliability. To ensure the enhancement of reliability, future investigations should undertake the task of revising these items. Despite our best efforts, the presentation of the problem scenario within our study fell short of our expectations. This limitation stemmed from various factors, such as a lack of familiarity with the PCI from the instructors' side. We decided to eliminate the "problem scenario" part from our curricular activity quality assessment survey. As a result, the participants' engagement with the problem scenario may have been compromised, potentially impacting the responses.

Additionally, the pretest with only five items falls short in fully assessing the desired Private AI skills. To enhance accuracy, incorporating a wider range of questions and also posttests to afford a more comprehensive understanding is advised. Finally, in the first iteration of this design study, the focus was primarily on the learner experience within a selected curricular module. For future research, greater emphasis should be placed on validating the design principles to advance a more robust conceptual framework. This would require larger sample sizes and a longer deployment across multiple modules. A scaled-up experiment could substantially demonstrate the potential of the curriculum to impact learner engagement and performance.

Conclusions and Further Research

This study reports on an effort to design, develop and implement a Private AI curriculum within a post-secondary CS setting grounded in PCI. The results showed that students considered the curriculum to be of high quality, with graduate students particularly valuing the pairwise collaboration. The results underscored the significant role of teachers in the learning process, with particular emphasis on bridging knowledge gaps and facilitating an effective learning environment. Learners expressed high motivation and interest in the subject, and their perceptions of competence were pivotal in triggering their motivation and interest. The findings provided insights to refine and improve the current curriculum, thus contributing to the ongoing efforts to optimize the quality of the curriculum offered in the ever-evolving field of Private AI. For future endeavors, it is recommended to implement the curriculum across different universities or educational contexts and bigger classrooms, using longitudinal studies to cover broader range of Private AI module topics. To improve reliability of the instruments, future investigations are fundamental to revise the items to better align with this specific context. Finally, it is recommended to conduct further research to learn how structured training on collaboration and problem-solving strategies might improve student's collaborative efforts. As the next step, we plan to conduct an in-depth case study analysis to examine pairwise collaborative activities to explore how learners navigate problem-solving tasks.

Acknowledgements

Availability of Data and Materials

The datasets used and/or analyzed during the current study are available from the Principal Investigator or Co-Principal Investigator on reasonable request.

Declaration of Conflicting Interests

The author(s) declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

Funding

The material is based upon work supported by the National Science Foundation (NSF) under Grant No. [Blinded for review]. 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.

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