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Bridging the AI Skills Gap through AI-Focused Course-Based Undergraduate Research

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Abstract

The rapid expansion of the artificial intelligence (AI) domain has outpaced the rate of course, major, and program revisions within applied computing fields, such as Information Technology, Information Systems, and Data Science. Consequently, a widening gap is being created between the competencies required by industry and the training provided by conventional academic programs. Course-based undergraduate research experiences (CUREs) offer a promising solution by blending foundational classroom learning with hands-on experimentation and skill development through student-driven research projects. This paper aims to replicate an existing information systems CURE model by focusing on enhancing AI education. This CURE model integrates core applied computing field competencies, such as project management and systems analysis and design, with applied AI techniques to construct a cohesive experiential learning structure. This project was implemented in a 200-level required course focused on hardware and software concepts across two semesters (three sections). Analyses included comparing AI and machine learning literacy at the beginning and end of the semester, which showed significant improvement, and a modified project reflection questionnaire adapted from the Persistence-in-the-Sciences (PITS) instrument. The PITS survey data were partially consistent with the literature on the potential positive impact of CUREs on persistence in AI/ML research and careers.

Keywords: AI Education, Course-Based Undergraduate Research Experiences (CUREs), Applied Computing, Experiential Learning

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1. INTRODUCTION

It is abundantly clear that artificial intelligence (AI) is reshaping economies, societies, educational practices, and curriculum needs (Brynjolfsson & McAfee, 2014). Higher education institutions face a significant challenge because the speed of AI advancement surpasses that of traditional curriculum development cycles (García-Peñalvo et al., 2021). Applied computing fields in non-R1 institutions face additional challenges due to limited resources to engage in homegrown, cutting-edge AI research that would expedite curriculum revisions. Employers increasingly seek graduates who possess not only technical proficiency but also higher-order skills, such as complex problem-solving, adaptability, critical thinking, effective communication, and the ability to collaborate on ambiguous, real-world challenges (Branger et al., 2015; Deming, 2017). Traditional pedagogical approaches may fall short in cultivating these essential competencies, leading to a potential skills gap between academic preparation and industry expectations. Course-based undergraduate research experiences (CUREs) allow instructors to focus on core concepts while also engaging students in creative problem-solving and technical exploration beyond conventional curricula. By empowering students to design and execute their own AI-focused research projects, CUREs cultivate critical skills, such as collaboration, critical thinking, and adaptability, which are essential for success in the fast-evolving professional landscape. In the science disciplines (e.g., biology, physics), educators have long explored course-based undergraduate research experiences (CUREs), which create a dynamic, engaging, and authentic learning environment. While traditional undergraduate research experiences (UREs) often occur outside the standard curriculum (e.g., summer research programs, independent studies), CUREs embed these experiences within the structure of a credit-bearing course (Auchincloss et al., 2014; Dolan, 2016). CUREs also address potential equity issues surrounding traditional research experiences and broaden access to undergraduate research (Bangera & Brownell, 2014). While widely adopted in STEM fields such as the biological sciences and chemistry (Hatfull, 2010; Wei & Woodin, 2011), CUREs are less common in computing fields (Bekerring, 2024); however, numerous studies show that undergraduate students exposed to research develop a deeper understanding of the scientific process and are more likely to complete their degrees and pursue graduate studies (Hathaway et al., 2002). This paper proposes and details a CURE model specifically tailored for AI education within applied computing programs. Our AI-focused CURE model synthesizes essential components from project management (PM), systems analysis and design (SAD), and hardware interaction, alongside core applied AI concepts. The implemented CURE emphasizes the principle of student agency, empowering students to define, design, and execute their own AI-focused research projects. This student-driven approach allows instructors to focus on foundational concepts and mentorship and encourages learners to engage deeply in creative problem-solving, technical exploration, and interdisciplinary thinking that extends beyond typical course boundaries. Our AI-focused CURE was implemented in a 200-level required course and focused on a structured yet flexible design, integrating multiple core computing competencies, offering a forward-thinking strategy to effectively evolve the curriculum and prepare students for the complexities of the modern AI-driven world. By blending foundational learning with hands-on, student-driven research, this integrated CURE model seeks to: (1) bridge the AI education gap in the curriculum; (2) develop critical workplace and lifelong learning skills; (3) cultivate essential attributes linked to STEM persistence, such as project ownership and self-efficacy (Hanauer et al., 2017); (4) provide a replicable model adaptable to various applied computing courses and institutional contexts. The following sections will delve into the theoretical underpinnings and relevant literature supporting this approach, provide a detailed description of the proposed AI-focused CURE model and our implementation of it, outline the persistence-in-the-AI assessment adapted from the Persistence in the Sciences assessment instrument, and discuss results and potential future replications and advancements of the model.

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1. LITERATURE REVIEW

The rapidly growing AI landscape dictates program evolution and curricular revisions. In this work, we build upon the literature on course-based undergraduate research experiences to advocate for infusing AI into existing courses. This approach can effectively counter or complement the more common strategy of creating new courses, majors, sequences, tracks, and certificates.

CUREs for Advancing in AI Skills in Applied Computing Fields

Applied computing programs are crucial pipelines for AI talent, and AI knowledge and competencies cannot be constrained to specific sequences or certificate programs; they must be ubiquitous. AI-enabled components are integrated into larger systems, requiring core competencies such as systems analysis and design and project management to ensure successful implementation consistent with the goals and needs of stakeholder groups (Valacich & George, 2020; Schwaber & Sutherland, 2020). The AI-focused CURE model introduced in this paper aims to cultivate both SAD and PM skills while fostering independent research.

Harnessing the Power of Undergraduate Research Experiences

Undergraduate Research Experiences (UREs) encourage students to move beyond consuming information and participate in the process of knowledge creation (Buckley and Kuh, 2009). Research literature reports the benefits of UREs, including enhanced critical thinking and problem-solving skills, increased understanding of the scientific process, clarification of career aspirations, improved self-confidence and self-efficacy, and higher rates of persistence in STEM fields and pursuit of graduate studies (Lopatto, 2007; Seymour et al., 2004; Russell et al., 2007). While traditional UREs offer significant benefits, their reach is often limited. CUREs integrate the core elements of a research experience into existing courses, thereby broadening participation (Dolan, 2016; Auchincloss et al., 2014). CUREs counter URE access issues (Table 1) by embedding them in credit-bearing courses. Literature has demonstrated CUREs' positive impacts on student learning outcomes, attitudes toward science, self-efficacy, and persistence, particularly for students from underrepresented groups (Bangera & Brownell, 2014; Hanauer et al., 2016; Rodenbusch et al., 2016).

Table 1. CUREs counter common access issues of UREs (Bangera et al., 2014)

Faculty	Assessment of Mentorship and Preference for the "Best" Students Unconscious Societal Bias
Students' self-selection (or lack thereof)	Awareness of Existing Research Opportunities Awareness of the Possible Benefits of Research Experiences Awareness of Cultural Norms Associated with Scientific Research Perceived Barriers to Interactions with Faculty Financial and Personal Barriers

Designing CUREs for applied computing fields requires careful consideration of what constitutes research and discovery, such as novel applications of generative AI models in building secure hardware-AI prototypes.

Integrating Core Computing Competencies in AI CUREs

In the 200-level hardware and software course, the CURE model integrated PM, SD, and Applied AI and hardware. AI-hardware projects introduced additional complexity that required incorporating SAD and PM competencies. SAD competencies ensure students consider the broader context of their AI solutions, including user requirements, design, modeling system interactions, and envisioning an appropriate scope (for the duration of the project) for their working prototype. PM knowledge areas equip students with tools to manage the uncertainty and iterative nature of research and development projects. Students were expected to decompose their envisioned goals into smaller tasks, estimate effort, track progress, recognize and manage risks, and maintain communication with the instructor and/or their team members (Javadi et al., 2025). Explicitly including elements of SAD and PM provides a more holistic experience in the design of CUREs in applied computing fields.

State-of-the-Art AI-Focused Experiential Learning

Our AI CURE model counters passive, lecture-based instruction (Freeman et al., 2014) by emphasizing experiential learning (Kolb, 1984), which fosters concrete experience, reflective observation, abstract conceptualization, and active experimentation. The AI CURE framework creates environments where students actively construct knowledge by tackling their unique problems or projects. The implemented CUREs position student-driven research projects as the

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central concrete experience around which learning occurs.

Mentoring and Modeling to Cultivate Independence and Persistence

The AI CURE model implemented here leverages near-peer mentoring and modeling to address cognitive, emotional, and other bottlenecks, including implicit bias. We employed two strategies: (1) Near-peer modeling, where advanced peers demonstrate workflows and troubleshoot in mentoring sessions, guiding less experienced students. This approach effectively mitigates cognitive and emotional challenges in project-based learning (citations). Near peers, having recently navigated similar challenges, enhance self-efficacy and motivation, provide practical advice, clarify the trial-and-error process, and reduce fear of failure and lack of confidence. (2) Instructor modeling, which is continuous and comprehensive: instructors integrate examples from their own project-based research, delving deeper into relevant topics during class discussions. They demonstrate how to train, test, and deploy models, as well as how to handle bottlenecks and setbacks in the project life cycle.

3. ASSESSING PERSISTENCE IN THE AI-RELATED FIELDS

To assess the effectiveness of undergraduate research, we examined students' attitudes, beliefs, and identities related to the field. The Persistence in the Sciences (PITS) survey (Hanauer et al., 2017), a validated instrument designed for Course-based Undergraduate Research Experiences (CUREs), measures key constructs linked to STEM persistence. The PITS survey evaluates Project Ownership (Emotional and Content), Self-Efficacy, Science Identity, Scientific Community Values, and Networking, providing valuable metrics for understanding the affective and cognitive impacts of research experiences.

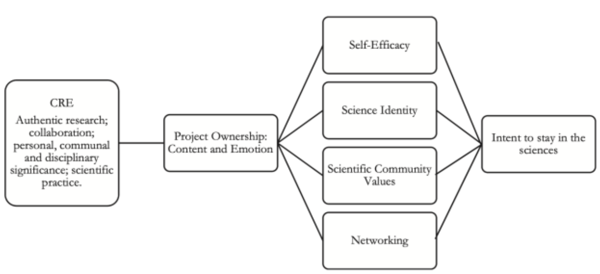

Figure 1. PITS constructs and relationships (Hanauer et al., 2016)

Our data suggest that fostering capability (self-efficacy) and belonging (identity) are critical for retaining students in the challenging and rapidly evolving field of AI. The PITS survey was adapted to explore persistence in AI-related research and career aspirations. Measurement items are listed in Table 2.

Table 2: Examples of PITS adapted for the IT field

PITS construct	sample modified PITS measurement item
project content	The findings of my AI and Microelectronics research project gave me a sense of personal achievement.
Emotions	I feel delighted about my research project.
self-efficacy	I am confident that I can use technical skills to solve a problem. (tools, platforms, and techniques)
IT community values	A person who thinks discussing new ideas between IT professionals is important.
Networking	I have discussed my research project in this course with my parents (or guardian) or family friends.
Identity in the IT world	I have come to think of myself as an IT researcher.
Intention to persist	How likely are you to pursue research projects at the intersection of applied AI/ML areas? How likely are you to pursue job positions or graduate degrees at the intersection of applied AI/ML areas?

4. COURSE DESIGN

CUREs not only enhance students' self-efficacy and connection to the field but also leverage the collective intellectual capital of the classroom and independent research to build richer teaching and learning experiences. This section describes the major pedagogical elements of our CURE implementation. Our course design incorporated elements listed in the previous sections.

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Research-based Atomic Learning Activities

These are very small assignments that expect students to research and create their unique deliverables instead of solving a problem defined by the instructor for the entire class. These atomic assignments are inherently research-based. An example of the atomic activities involved students exploring hardware inventory in their personal environments (dorms, apartments, or family homes) for hardware devices, identifying the processor design and model, and sharing a brief history of the device (e.g., year on the market, major consumer use cases). Students were required to include a picture of the device in the environment, which led to authentic, engaging, and diverse discussions in class.

Individual Research and Prototyping Work

The 200-level course required two research and prototyping projects focused on AI and hardware. Each student was required to start the semester with a vision document, which fostered an immediate sense of self-exploration and ownership of the learning experience in the course. The vision documents were reviewed and returned with formative feedback. Students embarked on their six-week individual project, which required research, trial and error, and extensive hardware-software pipeline technical troubleshooting. The project concluded with a live demo. Each student was required to document the project's technical steps in a GitHub repository and include a short video focusing on major steps and tips for the community.

Mentoring and Cognitive Modeling

Cognitive modeling was twofold. First, the regular lectures contained atomic research and prototyping workflow elements. An example of such modeling was training and testing models and working with APIs. Second, more experienced near peers from previous semesters modeled and conducted mentoring sessions for the students. This has been shown to effectively address both cognitive and emotional challenges in project-based learning (Collins et al., 1991). Near-peers who have recently navigated similar challenges can enhance self-efficacy and motivation, offer practical advice, decode challenges and opportunities of trial and error, and thereby reduce the fear of failure and lack of confidence. This two-tier mentoring element is based on the cognitive apprenticeship model, which is used to gradually build student independence in AI/microelectronics. Near-peers model experimentation with tools, demonstrating workflows and troubleshooting, which helps students transition to their course project development. Throughout the semester, faculty model research processes while encouraging more independent decision-making. Finally, students advance to primarily self-directed work with periodic check-ins with the instructor, reflecting real-world professional practice. This structured progression scaffolds students' journey from dependent to independent learners while ensuring support at critical junctures in their technical development (Dennen & Burner, 2008).

Group Research and Prototyping Work

In this CURE implementation, students chose their groups based on their individual project work and interests. For some students, the decision was clear during the individual project work when they exchanged ideas with their classmates and requested or offered help on similar problems or issues they were facing. Other students made their decisions during the project demos when they learned from other projects and decided to pivot and join a project with different trajectories to maximize their exposure to new challenges and, in turn, their learning.

5. DATA COLLECTION AND PRELIMINARY RESULTS

The AI CURE was implemented in two separate semesters with different cohorts of students engaging in AI-Hardware research taking the same course (in Fall 2024 and Spring 2025). This manuscript reports preliminary results of one of the two semesters only. The students engaged in AI-focused CURES for one 16-week course. We conducted the PITS survey (Hanauer et al., 2016) at the end of the semester. We also conducted pre- and post-surveys focused on machine learning and AI literacy. The data was collected in three sections of a 200-level course across two semesters (one section in the fall, two sections in the spring), and this report includes the Spring 2025 dataset. The majority of the students were sophomores and juniors. Table 2 shows more details on the dataset size and demographic information.

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Table 2. Basic demographical information for all valid PITS responses (total number of students: 60)

Surveys submitted	58	Valid responses	53
Students' standing	5 freshmen 19 sophomores 22 juniors 5 seniors		
Majors	4 Computer Networking 10 Information Systems 1 Computer Science 38 Cybersecurity		
Gender	8 female 45 male		

The AI/ML literacy questions are listed in Table 3, and preliminary data analysis from one semester is shown below.

Table 3. AI/ML understanding survey

I can describe how machine learning models are trained.
I can describe how deep learning relates to machine learning:
I can explain how AI applications make decisions.
I can explain how reinforcement learning works on a basic level.
I can explain how sensors are used by computers to collect data that can be used for AI purposes.
I can explain what the term artificial neural network means.
I can explain how machine learning works at a general level.
I can explain the difference between supervised learning and unsupervised learning.
I can describe the concept of explainable AI.
I can describe how some artificial intelligence systems can act in their environment and react to their environment.
I can explain if media representations of AI (e.g., in movies or video games) go beyond the current capabilities of AI technologies.

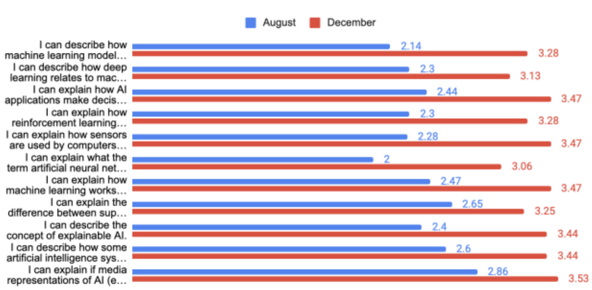

Figure 2: Spring 2025 AI/ML pre- and post-survey average on a 1-5 Likert scale (N-pre: 60, N-post: 57)

The p-value (1.23e-08) for the t-test indicates that the difference in students' self-reported perceptions of their understanding of AI concepts between August and December is statistically significant. To analyze the PITS survey data, we examined factor loadings of the latent variables on indicators; all were within the acceptable range. We examined the correlations among the latent variables, which are listed in Table 3.

Table 4. Spring 2025 correlation among latent variables

	1	2	3	4	5	6	7
Content (1)	1						
Emotion (2)	.814	1					
self-efficacy (3)	.714	.664	1				
Identity (4)	.634	.649	.486	1			
Community (5)	.595	.646	.465	.441	1		
Networking (6)	.641	.669	.494	.465	.452	1	
intention-to-persist (7)	.531	.548	.431	.409	.352	.789	1

Table 3 indicates that intention to persist is correlated with networking, content, and emotion at a higher level than with self-efficacy, identity, or community latent variables. This finding prompted an additional mediation analysis. The mediation analysis shows statistically significant total effects of project ownership-content and project ownership-emotions on intention to persist, but no statistically significant indirect effects through self-efficacy, community, identity, or networking constructs.

Table 5: Spring 2025 project ownership direct and indirect effect on intention-to-persist

Direct and indirect path analysis	Total effects Std. estimate, (std. error)	p-values
content → intention-to-persist (direct) emotions → intention-to-persist (direct)	0.335 (0.131) 0.434 (0.129)	0.007 <.001
content → intention-to-persist (indirect) emotions → intention-to-persist (indirect)	0.075 (0.079) 0.079 (0.080)	0.342 0.321

The primary data analysis shows a positive impact on perceived understanding of AI/ML concepts and positive effects of project ownership on self-efficacy, IT identity, community, networking, and intention to persist. However, our data analysis was not consistent with the proposed mediating effect of self-efficacy, IT identity, community, or networking on intention

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to persist.

6. CONCLUSIONS

In this paper, we share elements of theoretical and pedagogical AI-focused course design and structure that build upon the literature on course-based undergraduate research. We specifically leveraged CUREs to address the challenge and opportunity of the rapidly expanding knowledge scope in AI and machine learning. We implemented CUREs in three 200-level courses focused on hardware and software, employing experiential learning and individual and group research-focused work to surpass the learning outcomes achievable in a traditional lecture and lab course. We measured improvements in students' AI/ML literacy and the impact on their intention to persist in pursuing research and careers in AI/ML. Our work provides an example of how CUREs can be employed in applied computing fields at primarily teaching-focused campuses to enhance teaching and learning experiences, even for students in the early years of their undergraduate program. CUREs allow for exploring a constantly expanding knowledge landscape and can replace and/or complement a hasty approach to new course design or new sequence/major offerings that lead to inequitable outcomes, benefiting only those students who self-select the major, sequence, or new courses. We recommend educators leverage CUREs to evolve curriculum more holistically in response to the current dynamic technological developments in the AI field. CURE course designs are adaptable to future technological advancements, including the highly anticipated development of quantum computing.

7. REFERENCES

Ahmad, Z., & Al-Thani, N. J. (2022). Undergraduate Research Experience Models: A systematic review of the literature from 2011 to 2021. *International Journal of Educational Research*, *114*, 101996. https://doi.org/10.1016/j.ijer.2022.101996

Bangera, G., & Brownell, S. E. (2014). Course-based undergraduate research experiences can make scientific research more inclusive. *CBE---Life Sciences Education*, *13*(4), 602--606. https://doi.org/10.1187/cbe.14-06-0099

Bekerring, E. (2024). Course-based Undergraduate Research Experiences (CUREs) for Computer Science. *Proceedings of the ISCAP Conference, Baltimore, MD*.

Buckley, J. A., & Kuh, G. D. (2009). Reinventing undergraduate education: Engaging college students in research and creative activities. *The Review of Higher Education*, *32*(3), 419-420.

Collins, A., Brown, J. S., & Holum, A. (1991). Cognitive apprenticeship: Making thinking visible. American Educator, 15(3), 6–11.

Dennen, V. P., & Burner, K. J. (2008). The cognitive apprenticeship model in educational practice. Handbook of Research on Educational Communications and Technology, 3, 425-439.

Eagan, M. K., Jr., H., S., C., M. J., G., G. A., H., F. A., & Garibay, J. C. (2013). Making a difference in science education: The impact of undergraduate research programs. American Educational Research Journal, 50(4), 683--713.

https://doi.org/10.3102/0002831213482038

Good, J. M., Halpin, G., & Halpin, G. (2000). A promising prospect for minority retention: Students becoming peer mentors. Journal of Negro Education, 69(4), 375-383. https://doi.org/10.2307/2696252

Hanauer, D. I., Graham, M. J., & Hatfull, G. F. (2016). A measure of college student persistence in the sciences (PITS). *CBE---Life Sciences Education*, *15*(4), ar54. https://doi.org/10.1187/cbe.15-09-0185

Hathaway, R., Nagda, B., & Gregerman, S. (2002). The relationship of undergraduate research participation to graduate and professional education pursuit: An empirical study. *Journal of College Student Development*, *43*(1), 60--72.

Linn, M. C., Palmer, E., Baranger, A., Gerard, E., & Stone, E. (2015). Undergraduate research experiences: Impacts and opportunities. *Science*, *347*(6222), 1261757. https://doi.org/10.1126/science.1261757

Martin, A., Rechs, A., Landerholm, T., & McDonald, K. (2021). Course-based undergraduate research experiences spanning two semesters of biology impact student self-efficacy but not future goals. *Journal of College Science Teaching*, *50*(4), 33--47. https://doi.org/10.1080/0047231X.2021.12290516

Nagda, B., Gregerman, S. R., Jonides, J., von

ISSN: 2473-4901
v11 n6406

Hippel, W., & Lerner, J. S. (1998). Undergraduate student-faculty research partnerships affect student retention. *The Review of Higher Education*, *22*(1), 55--72. https://doi.org/10.1353/rhe.1998.0016

Rodenbusch, S. E., Hernandez, P. R., Simmons, S. L., & Dolan, E. L. (2016). Early engagement in course-based research increases graduation rates and completion of science, engineering, and mathematics degrees. *CBE—Life Sciences Education*, *15*(2), ar20. https://doi.org/10.1187/cbe.16-03-0117

Russell, S. H., Hancock, M. P., & McCullough, J. (2007). Benefits of undergraduate research experiences. *Science*, *316*(5824), 548--549. https://doi.org/10.1126/science.1140384

Schwaber, K., & Sutherland, J. (20222). The scrum guide. Accessed September 2025. https://mthi.vn/wp-content/uploads/2021/01/20210115-SCRUM-GUIDE-2020-VIE-THI.pdf

Seymour, E., Hunter, A. B., Laursen, S. L., & DeAntoni, T. (2004). Establishing the benefits of research experiences for undergraduates in the sciences: First findings from a three-year study. *Science Education*, *88*(4), 493—534. https://doi.org/10.1002/sce.10131.

Valacich, J. S., & George, J. F. (2020). Modern systems analysis and design, Hoboken.