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DeVry University Journal of Scholarly Research

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DeVry University Journal of Scholarly Research

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A message from the Provost

Artificial intelligence is rapidly changing how we work and what our graduates need to know to be successful in the workplace. Each of our disciplines is changing rapidly, and for DeVry University, this moment presents an important academic opportunity: to thoughtfully explore how AI can strengthen teaching and learning to prepare our students for a future in which technological fluency will be increasingly essential.

As we advance this work across the University, our faculty have an especially important role to play. The questions emerging around AI create rich opportunities for scholarship by examining its application within a particular discipline, exploring new approaches to teaching and assessment, designing case studies relevant to the workplace, and considering the ethical and responsible use of these technologies.

The *DeVry University Journal of Scholarly Research (DUJOSR)* provides an ideal forum for this type of inquiry and research. I encourage faculty to use the journal not only to share what you are learning, but also to ask new questions. Scholarship is one of the ways we turn curiosity into knowledge and put that knowledge into practice. Our commitment to impart practical learning is what differentiates us from other schools that provide plenty of theoretical knowledge and ultimately ensures that DeVry stays grounded in our commitment to student success.

I also want to recognize **Dr. Darryl Field** for his support of the *DUJOSR* and for his broader contributions to our academic community. Darryl's encouragement of faculty scholarship and his commitment to academic excellence have helped strengthen the journal and the culture of scholarship it represents. We are grateful for his leadership and wish him all the best in retirement.

I hope the work featured in this issue inspires you to continue the inquiry within your own classroom and discipline and turn that curiosity into a future contribution to the *DUJOSR*.

Shantanu Bose, PhD
Chief Academic Officer and Provost



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A message from the Managing Editors

We welcome the DeVry University community to the latest edition of the ***DeVry University Journal of Scholarly Research (DUJOSR, Vol. 10, No. 1)***.

In this issue we have a range of interesting and novel contributions from our colleagues in the Colleges of Business & Management (COBM) and Engineering & Information Science (EIS) and Liberal Arts & Sciences (LAS). AI and AI in higher education remains an important theme, beginning with our letters to the editor and in comments from the provost.

We are excited to include three EIS papers, a From the Classroom piece (LAS), a case study from the COBM, a Faculty-Students Collaboration, two letters, and we can again enjoy book reviews from the DeVry University community of scholars. Our thanks to all the authors who provided submissions: Joe Louderback, Mohamed E. Brihoum & Natalie Waksmanski-Krynski, Geneviève Sapijaszko & Simon Obeid, Penn Wu, Dianna Robison & Veronica (Ronnie) Schreiber, Mary Sanders, Daniel Isac Gomes, Judith Kelso, Michael Lane, & Emre Ozmen, Nick Lebredo, and Shawn Schumacher.

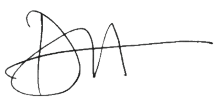
We would like to take this opportunity to congratulate our community of talented scholars participating in the 2026 DeVry Faculty Symposium: **Education Reimagined: AI and the Future of Learning**. The tracks include Industry Partnerships and the Future Workforce; Teaching and Learning in the Age of AI; Research, Innovation, and Emerging Technologies; Human–AI Collaboration and Creativity; The Unintended Consequences of AI in Education; and DeVry Care. Huge thanks to the Symposium Steering Committee, led by Team Captain Teresa Hayes. The team includes Vicky Kim, Mike Reitzel, Sheila Sampath, Jim Schneider, Christine Halsey, Joan Snyder, Louis Freese, Michelle Cranney, Paula Herring, Kim Lana-Finn, Shawn Schumacher, Ellen Jones, and Mike Stamos.

We want to invite you to contribute to DeVry University's vision for the future of online education in business, healthcare, and technology in a future issue of the Journal. We encourage all members of our community to explore the many opportunities to publish, serve as a reviewer, or join the editorial board. If you have previously submitted a paper but have not yet completed the revisions, consider adding it to your "To Do" list as it should help benefit your IPP!

We acknowledge the continued support of the provost, and the leadership of Sandy Kampenga, the continued dedication of the editorial board and peer reviewers, and the very important work and generosity of our contributors. We thank our now-retired Associate Provost Darryl Field for his unwavering support.

Please visit the *DUJOSR* via the library and CTE, and in the Journal archive in the DeVry University Newsroom: https://www.devry.edu/newsroom/academic-publications.html

Deborah Helman, PhD
Co-Managing Editor



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JOURNAL INFORMATION

The DeVry University Journal of Scholarly Research (ISSN 2375-5393 1) is a semi-annual multi-discipline, peer-reviewed, journal devoted to scholarship and education research.

The journal is the work of the faculty, staff and administration of DeVry University. The views expressed in the journal are those of the authors and should not be attributed to the sponsoring organizations or the institutions with which the authors are affiliated.

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MANUSCRIPT SUBMISSIONS INFORMATION

The journal welcomes unsolicited articles, case studies, reviews, and letters on scholarship, education research or related subjects. Text and citations should conform to APA style as described in the Publication Manual of the American Psychological Association (7th ed.). Because the journal employs a system of anonymous peer review of manuscripts as part of its process of selecting articles for publication, manuscripts should not bear the author's name or identifying information.

Electronic submissions of manuscripts (MS Word) and all other communications should be directed to: DUJOSR@devry.edu

EDITORS AND REVIEWERS

DeVry faculty who wish to apply for positions on the Journal's board of editors or as reviewers of manuscripts should contact Deborah Helman or Michael Bird.

PEER REVIEWERS FOR THIS ISSUE

The following DeVry faculty served as peer reviewers for this issue. We thank them for their service.

Paula Herring, PhD
Jacqueline Lang, PhD
Jacqueline Saldana, PhD
Bhupinder S. Sran, PhD
Chao Ying Wang, PhD

INSTITUTIONAL REVIEW BOARD

DeVry University has an Institutional Review Board (IRB) to protect the rights and welfare of humans participating as subjects in a research study. The IRB ensures the protection of subjects by reviewing research protocols and related materials. DeVry University's colleagues and students who want to conduct research must first contact the IRB for an application. Once received, the IRB will review the application and supporting materials to determine if all criteria have been met before approving the research. In support of helping colleagues and students gain an in-depth understanding of ethical research processes, the IRB requires CITI certification for all applications. The application is available on the CTE website. Applicants should contact Sandy Kampenga skampenga@devry.edu for approval and reimbursement of the CITI certification costs.

For additional information, you can contact the DeVry University IRB through the following email address: dvuirb@devry.edu.

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Call for Papers, Spring 2027 Issue

The *DeVry University Journal of Scholarly Research* (DUJOSR) continues to expand its pages to include a variety of publishing opportunities for faculty. Academic scholarship remains a staple for the journal, but new categories include Case Studies, Book Reviews, Course Reviews, Letters to the Editor, and From the Classroom, and Faculty-Student Collaboration sections, in which faculty can share vital experiences and best practices. These categories of submission are fully described below. Specific deadlines and instructions for submission conclude this "Call for Papers".

ACADEMIC SCHOLARLY ARTICLES

For the **Spring 2027** issue, we continue to solicit "working papers" (3000 to 5000 words) in our scholarly article category.

Papers of all types are welcome including theory, empirical, or methodology papers, as well as literature reviews, from both positivist and naturalistic traditions. Research- and evidence-based papers emphasizing practical relevance that resonate with our readers are preferred. We regard submissions as "working papers" that can be submitted to other journals for consideration (but have not been previously published elsewhere).

The review process requires that each paper is coded and blind reviewed by two peer reviewers with expertise in the author's discipline. Faculty volunteers (for whom profound gratitude is expressed) comprise the peer review board. Final publication decisions are made by the editorial board, consisting of College and Managing Editors.

Authors who have previously submitted academic scholarly papers for past issues are encouraged to re-submit their revised papers. Papers should be sent with an additional document that specifies detailed responses to reviewers' and editors' feedback.

CASE STUDIES

DUJOSR solicits case studies (ranging from approximately 500-word short cases, to 1000 to 3000-word long cases) that have not been published elsewhere but are considered "working papers." The purpose of this initiative is to create a repository of case studies that can be used by faculty to teach DeVry University graduate and undergraduate courses. Our aim is to provide students with a unique and valuable learning experience that has been generated by our faculty.

Case studies of all types are welcome, including multi-media. We would prefer case studies that emphasize practical relevance that resonate with our faculty and students. Case study submissions must also be supported by a set of directions, i.e., Faculty Teaching Notes. The teaching notes must indicate the relevant courses and TCOs associated with the case study, as well as suggested question strategies and pedagogical practices.

The case study should be significant, complete, compelling, inclusive of alternative perspectives, qualitative, sufficiently evidenced, aligned with one or more Course Objectives, and written with accuracy and relevance.

The review process for case studies is the same as for academic scholarly papers. Case studies will be evaluated on the following criteria:

- Timeliness of case & relevancy (tied to 1 or more Course Objectives)
- Theoretical framework, and practical applications
- Opportunity to expand knowledge,
- Implications for field of studies
- Case notes for faculty
- Writing quality: Clarity, conciseness, and organization, grammar and mechanics,
- APA format, including in text citations and reference page.

There is no submission deadline; case studies will be accepted on an ongoing basis.

BOOK REVIEWS

Book reviews continue to be a regular feature in the journal pages. They are an important part of scholarly life. They alert colleagues to new developments in the academy, foster discussions that can lead to new scholarship, and ultimately provide us with both a broader and deeper view of the world, which we in turn can share with our students.

Reviews of either fiction or non-fiction works should adhere to the following publication guidelines:

1. Reviews should be between 500 to 1000 words in length, double spaced, and include the following: author, title, place of publication, publisher, year, price, page length (including introduction and text), and International Standard Book Number (ISBN).
2. Reviews should include a brief summary of the scope, purpose, content of the work, and its significance in the literature of the subject. Reviews should evaluate the strengths and weaknesses of the work as well as attend to its use of sources, including documentation, methodology, organization, and presentation.
3. Reviews should be fair, balanced, and treat authors with respect.
4. A signed permission form to publish a review is required.

COURSE REVIEWS

Course reviews should pertain to an academic course attended by the author of the review.

1. Reviews should be between 500 to 1000 words in length and provide an overview and critique of the course content, name, location, supporting organizations and date.
2. Reviews should include a summary of the scope, purpose, content of the course content, and its academic significance. Reviews should evaluate the strengths and weaknesses of the course as well as attend to its use of documentation, methodology, organization, and presentation.
3. Reviews should be fair, balanced, and treat authors with respect.
4. A signed permission form to publish a review is required.

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LETTERS TO THE EDITOR

Letters to the Editor are a welcome addition to the journal pages. Letters that reply to or extend academic scholarship published within *DUJOSR* pages are particularly welcome, as these add rich texture and dialogue to ideas presented. Letters should be professional, well-tempered, and engage with content meaningfully. Letters that do not necessarily attend to previously published work but are timely and relevant are also welcome.

Letters responding to published articles in *DUJOSR* should identify the month and year of the article, review, or previous letter on which it is commenting. The full title of the article, review, or letter as well as the author(s) should be included. Letters should be double-spaced and 500 to 1000 words in length. Letters may express well-tempered opinions but should include citations in cases where academic integrity requires documentation. Letters should be fair, balanced, and treat authors with respect.

FROM THE CLASSROOM

This section of the journal is newly offered to faculty who have rich pedagogical experiences worthy of sharing with a larger audience. Papers in this category may use research to support ideas but may also consist of valuable experiences about which research may not have yet caught up. Well-crafted papers that demonstrate increased student engagement in the classroom are particularly prized. In this category, the recommendations for length are 750 to 1000 words, but longer papers of exceptional quality and relevance will be considered. Content should seek to express pedagogies that transcend the commonplace or that provide an interesting new spin on well-trod best practices.

FACULTY-STUDENT COLLABORATIONS

Collaborative faculty-student publications provide an opportunity for students to engage in scholarship and learn how to publish as part of a collaborative effort. This section of the journal is newly offered to faculty who have the opportunity to encourage students to prepare papers from course projects or assignments. In this category, the recommendations for length are 750 to 1000 words for case studies, and 2500 to 3000 words for research papers. Content should seek to express domain (related to the course taken) expertise that transcends the commonplace or that provides an interesting new spin on traditional approaches. Submissions are not peer reviewed - they are dealt with by the editor. Faculty members are expected to act as mentors, collaborators, or consultants for the students' scholarly work.

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EDITORS' INSTRUCTIONS FOR AND SUBMISSION AND DEADLINES

All submissions are expected to follow the APA 7th edition style sheet. APA source materials are available in the DVU LibGuide APA/Writing Center. In addition, the APA publishes a handbook advising writers on all aspects of the publishing process: Publication Manual of the American Psychological Association, Seventh Edition (2020). Please consult the following websites:

DVU LIBRARY:
https://libguides.devry.edu/APA

The American Psychological Association (APA):
https://www.apa.org/
https://apastyle.apa.org/style-grammar-guidelines

Please note that *DUJOSR* allows the use of AI-generated content in all its submissions categories, but faculty and student authors must acknowledge the use of such content as relevant and as appropriate so that it is clear to readers which content is generated by AI and which is by the authors themselves. In addition, authors are expected to correct any AI-generated factual content or APA documentation errors before submission. For more details about how to acknowledge AI-generated content, see the "How to Cite AI Tools" section of the DVU LibGuide on Artificial Intelligence – Faculty. Please consult the following website:

DVU LIBRARY:
https://libguides.devry.edu/AI

The submission deadline is March 1ST, 2027. Please submit your work and a Turnitin Report in any category to Managing Editors, Deborah Helman and Michael Bird, at DUJOSR@devry.edu.

The Managing Editors reserve the right to edit all submissions in any category of submission for length, tone, and content, over and above recommendations made by peer reviewers and College Editors.

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Letter to the Editors:

The Intelligence Paradox of AI in Higher Education

Dear Editors,

As our university continues to integrate artificial intelligence tools into classroom instruction, I believe it's crucial that we understand a fundamental paradox that could reshape how we approach AI-assisted learning.

Raymond Cattell's seminal research from the 1940s distinguished between two types of human intelligence: fluid intelligence (our raw problem-solving and pattern recognition abilities that peak in our twenties) and crystallized intelligence (our accumulated knowledge and skills that grow throughout our lifetime). This framework has guided educational psychology for decades.

However, Large Language Models present us with an unprecedented inversion of this intelligence trajectory. Unlike humans, who begin with strong fluid intelligence and gradually build crystallized knowledge, AI systems start with vast crystallized intelligence—having been trained on humanity's collective knowledge base—but demonstrate significant limitations in fluid intelligence when faced with novel problems or unfamiliar contexts.

This has profound implications for classroom integration:

The Challenge: Students may become overly reliant on AI's extensive factual knowledge while potentially under-developing their own fluid intelligence—the very capacity for creative problem-solving and adaptive thinking that defines innovative scholarship.

The Opportunity: This intelligence complementarity suggests that human-AI collaboration in educational settings could be uniquely powerful. Students bring fluid adaptability and novel reasoning capabilities, while AI contributes comprehensive knowledge synthesis and information processing.

The Pedagogical Question: How do we structure AI-assisted learning to enhance rather than replace students' development of fluid intelligence? Perhaps we should focus on using AI as a knowledge partner while deliberately designing assignments that require the kind of novel reasoning and creative adaptation that AI currently struggles with.

As we move forward with AI integration, we must ensure that we're not inadvertently creating a generation of students who, like current AI models, possess extensive crystallized knowledge but lack the fluid intelligence necessary for true intellectual innovation.

I encourage our academic community to consider this intelligence paradox as we develop AI policies and pedagogical approaches. The goal should be leveraging AI's strengths while preserving and enhancing the uniquely human cognitive capabilities that drive discovery and learning.

Sincerely,

Mohamed E. Brihoum, PhD
DeVry University, Florida

Cattell, R. B. (1943). The measurement of adult intelligence. *Psychological Bulletin,* 40(3), 153–193.

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Letter to the Editors:

Accessing AI Library Resources

Dear Editors,

The DeVry University Library offers a range of resources to assist students with navigating the world of artificial intelligence. The Library's Student Guide on Artificial Intelligence (https://libguides.devry.edu/studentAI) provides a brief overview of the history of AI, resources for making the best use of AI, including a sample of eBooks in the library's collections, rules for proper citation of AI tools, and guidance on prompt engineering and evaluation of AI tools and results. The Guide also includes a list of our subscription databases that provide AI-enhanced search or analysis options.

The AI-enhanced library databases include Britannica Academic, EBSCOhost (and related databases), O'Reilly Media, Statista, IBISWorld, and the ProQuest One suite. The ProQuest One and IBISWorld databases offer AI tools for summarizing, evaluating, and interrogating sources, as well as offering expanded search options based on retrieved content. The other databases listed provide AI-enhanced search in addition to traditional lexical search, which allows for expanding searches and extracting difficult-to-find information from the databases.

The DeVry librarians demonstrate effective use of these AI features for our students during the several presentations offered each term. The library's presentations include targeted instruction sessions for specific courses, general sessions for a wider audience (e.g., marketing, Keller, APA), and the Date with a Database series. The library presentations not only share resources with students but also include information literacy instruction to help our students become effective, life-long learners.

Faculty can also learn about our AI-enhanced databases and other resources by attending the library's presentations. The presentation schedule is shared with faculty via email every term and is also posted on the library website. Faculty who wish to delve deeper into the intersection of information literacy and artificial intelligence may want to enroll in the Information Literacy Workshop for Faculty, offered once or twice annually by the library team. The Information Literacy Workshop is updated on a rolling basis, and the latest iteration includes discussion of information literacy and artificial intelligence in every module. Contact Joe Louderback or Patti Meyer for more information on the Information Literacy Workshop.

Sincerely,

Joe Louderback, Librarian
DeVry University

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From Emerging to Fluent AI Users: A Framework for AI-Enhanced Engineering Learning

Mohamed E. Brihoum & Natalie Waksmanski-Krynski
College of Engineering & Information Sciences

Author Note: Mohamed E. Brihoum, PhD, Senior Professor, DeVry University, Orlando, FL, & Natalie Waksmanski-Krynski, PhD, Professor, DeVry University, Chicago, IL

ABSTRACT

This paper presents descriptive findings from an exploratory, observational study of AI fluency development following implementation of a structured AI framework in a first-year online undergraduate engineering course. As generative AI tools become common in engineering classrooms, instructors face a practical challenge: students frequently use AI for answer confirmation rather than for disciplined verification, assumption testing, or design exploration. To address this gap, a four-role AI framework (Collaborator, Foil, Catalyst, and Interrogator) was introduced to guide students toward verification-oriented and reflective use of AI during circuit analysis and design tasks.

This study examined AI fluency development in two parallel online first-year electronics course sections (N ≈ 120). Both sections received identical instruction, assignments, and AI guidance materials, yet diverged substantially in AI fluency progression. During Weeks 1–3, students in both sections used AI primarily for explanations and answer checking. In Week 4, Section A produced the first student examples meeting Stage 4–5 criteria demonstrating multi-method verification, adversarial questioning, and integrated use of multiple AI roles; these examples diffused broadly across the section. Section B, which had fewer early peer models and a substantially higher proportion of full-time working students (~68% vs ~22%), showed little movement beyond basic answer confirmation.

The findings suggest that advanced AI use may be influenced by multiple interacting conditions, including the visibility of strong peer examples, alignment of AI roles with engineering verification practices, employment-related time demands, and other student or section characteristics. The results provide practice-focused strategies for engineering instructors, including making advanced AI reasoning visible early in the term, embedding verification expectations directly into assignments, and framing AI roles as tools that strengthen engineering judgment rather than replace it.

Correspondence regarding this article should be addressed to Dr. Brihoum at mbrihoum@devry.edu, or Dr. Waksmanski-Krynski at nwaksmanski@devry.edu

Keywords: AI users, AI enhanced learning, practice-focused strategies, engineering instructors

INTRODUCTION

AI tools such as ChatGPT and Claude are becoming common in engineering courses. A practical concern is that students may use these tools primarily to check answers rather than to question assumptions, compare methods, or explore alternative solutions. Engineering education literature emphasizes complex problem solving, design reasoning, and analysis as important aspects of engineering preparation (Atman et al., 2007; Jonassen, 2000; National Academy of Engineering, 2004), while ABET criteria likewise emphasize problem solving, experimentation, analysis and interpretation of data, and engineering judgment (ABET Engineering Accreditation Commission, 2021). AI literacy frameworks and assessment models provide broader guidance for understanding, evaluating, and using AI (Long & Magerko, 2020; Ng et al., 2024), but they are not specifically designed around repeatable engineering verification workflows. Early observations in this study suggested that peer examples—not instructor demonstrations—might be associated with how students learned to use AI. This interpretation is consistent with social learning theory, which emphasizes learning through observation and modeling (Bandura, 1977).

This paper makes two contributions. First, it introduces an engineering-specific AI fluency framework consisting of four functional roles that map directly to engineering reasoning practices. Second, it examines peer modeling as one factor associated with the development of advanced AI use within course sections, while recognizing that employment status, available time, and other unmeasured characteristics may also contribute to observed differences. In this paper, peer examples refer to student-generated artifacts that demonstrate advanced AI behaviors; peer modeling refers to the process through which other students observe and may adopt those behaviors.

The following research questions guided the study:

1. How did students progress from basic to advanced AI use?
2. What role did peer examples play in shaping adoption?
3. What conditions supported or limited students' progression in AI fluency?

The observational evidence reported here is intended to inform instructional practice rather than establish causal claims. This study focuses on AI fluency development as an observable behavioral outcome and does not evaluate direct impacts on student learning or conceptual mastery.

AI FLUENCY FRAMEWORK

FOUR AI ROLES

The four roles introduced in this study (Collaborator, Foil, Catalyst, and Interrogator) were developed specifically for this work. Existing AI literacy frameworks and assessment models describe or measure broad competencies such as understanding AI systems, critically evaluating outputs, communicating with AI, and considering ethical issues (Long & Magerko, 2020; Ng et al., 2024). These resources are not designed to provide the specific, repeatable reasoning behaviors used here for engineering problem solving. The goal of the four-role model is to translate broader AI literacy concepts into practical actions that align with engineering workflows, including verification, assumption testing, and exploration of design alternatives.

Table 1 (next page) summarizes the four AI roles and shows how each aligns with Bloom's Taxonomy and its revision (Anderson & Krathwohl, 2001; Bloom, 1956) (Column 3) and with typical stages of AI Fluency (Column 5). Bloom's levels describe types of thinking, whereas the AI Fluency stages describe observable student behaviors in this course. The "Typical Stage" column indicates the stages in which each role was most commonly observed; it does not imply that a role is restricted to those stages.

Table 1 - Mapping AI Roles to Bloom's Taxonomy and AI Fluency

ROLE	PURPOSE	TYPICAL BLOOM FOCUS	EXAMPLE PROMPT	TYPICAL STAGE
Collaborator	Explain concepts	Remember, Understand	"Explain RC time constant."	2–3
Foil	Check for errors and challenge assumptions	Analyze, Evaluate	"Find mistakes in my solution."	3–4
Catalyst	Explore variations or design options	Apply, Analyze, Create	"What if I double R?"	4–5
Interrogator	Test understanding with questions	All levels	"Quiz me on filters."	4–5

The Bloom levels shown in the table are intended as a heuristic alignment, not an exclusive or exhaustive mapping. Each role can involve multiple cognitive processes. For example, Foil often includes elements of Apply when students carry out procedures and then ask AI to check their work, but we emphasize Analyze and Evaluate because the distinctive purpose of the Foil role is to interrogate assumptions and identify errors. Similarly, Catalyst can also draw on Understand, but we highlight its focus on Apply/Analyze/Create, where students explore variations and design alternatives.

Although some of the roles appear similar, each serves a distinct purpose in engineering reasoning. The distinctions between these roles are subtle but important for developing disciplined engineering habits. Foil and Interrogator both involve questioning, but they differ in who is being questioned. The Foil role asks AI to question the student's work by searching for mistakes or flawed assumptions, while the Interrogator role asks AI to question the student's understanding through quizzes or targeted prompts. Similarly, Collaborator and Catalyst both support exploration, but the Collaborator focuses on building understanding through explanations and analogies, whereas the Catalyst encourages design variation and "what-if" analysis to stretch the problem into new directions.

In practice, advanced users often blend these roles. For example, a student may ask AI to verify a calculation (Foil), then explore parameter changes (Catalyst), and finally request questions to test understanding (Interrogator). This integration of roles is characteristic of Stage 5 fluency and reflects how professional engineers use AI for multifaceted reasoning tasks.

Although the four roles can be adapted to other disciplines, they were deliberately designed to align conceptually with ABET expectations related to engineering problem solving, experimentation, analysis and interpretation of data, and the use of engineering judgment and tools.

For example, the Foil role operationalizes multi-method verification that is routine in engineering (hand calculation checked against AI, simulation, or measurement). Similarly, the Catalyst role supports iterative "what-if" exploration under performance, cost, safety, or manufacturability constraints, a core feature of engineering design cycles. These links to verification-intensive and constraint-driven engineering problem solving distinguish the present framework from broader AI-literacy models.

The framework is conceptually aligned with selected ABET expectations, but the present

study does not evaluate whether use of the framework improves achievement of ABET outcomes. That question remains for future empirical study.

FIVE STAGES OF AI FLUENCY

Students' progress from basic to advanced use through five stages:

1. Non-User – Does not use AI
2. Emerging User – Uses AI for explanations or answer checking
3. Developing User – Verifies solutions with two or more methods
4. Advancing User – Challenges AI and uses adversarial questioning
5. Fluent User – Integrates several AI roles in one reasoning process

The five-stage AI fluency progression was developed in this study to characterize observable progression in students' use and integration of the four roles during engineering tasks. Together, the four roles and five stages form a structured framework that links functional AI behaviors with developmental integration over time.

The four AI roles and the five stages operate at complementary but distinct levels within the framework. The roles define functional, prompt-level behaviors that students can apply during engineering problem-solving (e.g., verification, adversarial questioning, exploratory variation). The stages describe developmental progression in how intentionally and systematically those roles are integrated over time. Advancement reflects more deliberate and coordinated use of multiple roles, not simply more frequent AI use. In this way, the roles specify what disciplined AI use looks like, while the stages indicate how deeply those behaviors are embedded in practice.

The following section situates this framework within the broader AI literacy literature and clarifies how it advances prior scholarship.

RELATIONSHIP WITH EXISTING AI LITERACY FRAMEWORKS

Several AI literacy frameworks, assessment instruments, and policy-oriented resources have been proposed in recent years (Long & Magerko, 2020; Ng et al., 2024; UNESCO, 2021). Collectively, these resources address broad themes such as understanding AI concepts, critically evaluating AI systems and outputs, using AI effectively, and considering ethical and societal implications.

While valuable for general education, these resources are not specifically organized around the iterative reasoning and design processes characteristic of engineering problem solving (Atman et al., 2007; Jonassen, 2000). Broader educational literature emphasizes cognition, metacognition and critical thinking, and adult learning principles that can shape how learners engage with new tools and reasoning practices (Eisner, 1994; Knowles, 1984; Kuhn, 1999). In parallel, a systematic review of AI applications in higher education documented a broad range of uses while noting limited educator involvement and pedagogical reflection in much of the literature (Zawacki-Richter et al., 2019). Together, these literatures motivate a more discipline-specific approach to structuring AI use within authentic engineering problem-solving contexts. Representative examples include:

Long and Magerko (2020) define AI literacy as competencies for critically evaluating AI, communicating and collaborating with AI, and using AI effectively, providing a broad foundation for AI literacy rather than engineering-specific prompting routines.

- Ng et al. (2024) developed and validated an AI literacy questionnaire organized around affective, behavioral, cognitive, and ethical dimensions. The instrument provides a structured approach to assessing AI literacy, but it is not explicitly mapped to engineering workflows such as multi-method verification, assumption testing, or simulation-based validation.

- Knoth et al. (2024) examine prompt engineering as a skill for goal-directed use of large language models in higher education and report that higher-quality prompting predicts higher-quality LLM output. Their work supports explicit instruction in AI literacy and prompting but does not provide the engineering-specific, role-based workflow proposed here.
- UNESCO (2021) addresses AI and education primarily at the policy and system level, including ethical, societal, inclusion, and competency considerations; it is not intended as guidance for engineering-specific problem-solving workflows.

Unlike broader AI-literacy frameworks, the present model translates these goals into minimal, role-based prompting actions aligned with engineering verification and design workflows and conceptually consistent with ABET expectations related to analysis, experimentation, and engineering judgment.

The four-role model (Collaborator → Foil → Catalyst → Interrogator) provides a structured set of prompt-level behaviors that students can immediately apply while solving circuits, mechanics, or design problems.

METHODS AND COURSE CONTEXT

This study employed a descriptive, observational analysis of AI fluency development in two parallel online course sections. Both sections received identical instruction, assignments, and AI guidance materials. The design focused on documenting patterns of AI use as they emerged in student work rather than introducing experimental manipulation. The analysis focuses on aggregate stage transitions, milestone observations, and differences between sections rather than formal statistical comparisons.

COURSE AND STUDENTS

The study was conducted in Summer 2025 in an eight-week fully online electronics course enrolling 120 students across two parallel sections (Section A: 60 students; Section B: 60 students). During the first week, students were encouraged to post brief introductions in the online course forum. Many students voluntarily shared information about their employment status. These self-reported statements were used to categorize students as working full-time or part-time for descriptive comparison purposes. Based on these introductions, approximately 22% of students in Section A and 68% of students in Section B reported working full-time while enrolled in the course. This difference in employment status is treated as a major contextual factor when interpreting the section-level patterns. No other demographic variables were systematically collected or analyzed. Although additional background information was sporadically shared in introductions, it was not consistently reported and therefore was not used for formal analysis.

FRAMEWORK INTRODUCTION

In Week 1, students were introduced to the AI fluency framework through a short instructor video (12 minutes) that demonstrated how to use each of the four AI roles (Collaborator, Foil, Catalyst, and Interrogator) during typical circuit problem-solving steps. Students also received a written guide containing role-based prompt examples they could reuse while completing discussion posts and laboratory reports. Use of AI was encouraged, but it remained optional throughout the course.

DATA SOURCES

PRIMARY DATA SOURCES

Primary data consisted of student-generated written artifacts collected throughout the eight-week term, including:

- Weekly discussion posts
- Laboratory reports

No measures of academic performance or learning gains were collected or analyzed, as evaluating learning outcomes was outside the scope of this observational study.

Discussion posts were required for weekly assignments submitted by enrolled students across the duration of the course. Prompts emphasized explaining problem-solving approaches, reasoning processes, and

verification strategies rather than explicitly requiring discussion of AI. Although AI use was encouraged through structured coaching, it was not mandated. References to AI interactions therefore emerged organically when students described how they approached, verified, revised, or challenged their solutions.

Laboratory reports provided additional insight into student reasoning. These reports often documented calculation steps, simulation verification, component selection decisions, and—in some cases—explicit descriptions of AI-supported verification, adversarial questioning, or reverse prompting. Together, discussion posts and laboratory submissions provided a longitudinal view of students' evolving reasoning practices.

SECONDARY DATA SOURCES

Secondary sources were used to contextualize patterns observed in primary artifacts and included:

- Student emails referencing AI use or concerns
- Instructor memos documenting weekly observations
- Participation patterns and visible engagement trends

These materials were not coded formally but informed interpretation of engagement dynamics and resistance patterns.

CODING AND STAGE CLASSIFICATION

Each student artifact (discussion post or laboratory report) was evaluated independently and assigned to one of the five AI fluency stages using the rubric provided in Appendix B.

Because students submitted multiple artifacts during the eight-week term, a single student could appear at different fluency stages at different points in time. This allowed observation of changes in stage classification over time.

Stage classification focused on observable behaviors, including:

- Presence or absence of multi-method verification
- Documentation of AI interaction beyond answer confirmation
- Evidence of reverse prompting or self-questioning
- Explicit adversarial questioning of AI assumptions
- Degree to which reasoning processes were made visible

To support consistency in classification, a subset of artifacts was re-coded after an interval and compared with original stage assignments. The classifications were largely consistent, suggesting stable interpretation of the rubric over time.

Because this study is framed as reflective practice rather than formal experimental research, coding was conducted by the instructor-researcher and is intended to illuminate patterns rather than establish generalizable statistical claims.

IDENTIFICATION OF WEEK 4 PEER EXAMPLES

During chronological coding of discussion posts, the first examples that met criteria for Stage 4 or Stage 5 fluency appeared in Week 4 of Section A. These posts were labeled as "strong peer examples" because they satisfied explicit rubric indicators such as:

- Multi-method verification (manual, AI, simulation)
- Adversarial questioning or challenging AI's reasoning
- Reverse prompting to test understanding, and
- Integration of multiple AI roles in a single problem-solving sequence

The timing of their appearance was not based on instructor judgment during the course. It emerged naturally during the coding process when the first Stage 4–5 posts occurred. No Stage 4–5 posts appeared in Section B during the same week, which contributed to the divergence observed later in the term.

RESULTS

The results, presented in ***Table 2***, summarize AI fluency stage progression patterns across student artifacts (discussion posts and laboratory reports) collected throughout the eight-week course. Findings are reported using aggregate stage proportions, milestone observations (such as the first appearance of Stage 4–5 behaviors), and relative differences between sections. The goal is to describe observed patterns in AI fluency development rather than to conduct formal statistical comparisons. See ***Appendix A***.

Table 2 - AI Fluency Stage Progression Patterns Across Sections

COURSE WEEKS	SECTION A (OBSERVED PATTERN)	SECTION B (OBSERVED PATTERN)
Weeks 1–3	Stage 1–2 dominant	Stage 1–2 dominant
Week 4	First Stage 4–5 artifacts appear	No Stage 4–5 artifacts
Weeks 5–6	Stage 3 behaviors diffuse	Stage 2 remains dominant
Weeks 7–8	Substantial Stage 4–5 representation	Minimal movement beyond Stage 2

OVERALL ADOPTION PATTERN

Both sections began the course with similar AI use patterns during Weeks 1–3, with most discussion posts classified as Stage 1 or Stage 2. The divergence between sections first became visible in Week 4, when Section A students posted the first examples meeting Stage 4–5 criteria. No comparable advanced-stage posts appeared in Section B during that same period. By Weeks 7–8, the difference between sections was substantial:

- Section A: 48% of posts were classified as Stage 4–5
- Section B: 4% of posts were classified as Stage 4–5

These proportions reflect a sustained shift in advanced AI role integration in Section A that was not observed in Section B.

Chronological coding showed a consistent sequence of observations: initial similarity in Weeks 1–3, the first Stage 4–5 artifacts in Section A during Week 4, and substantial divergence between sections by Weeks 7–8.

EXAMPLES OF STAGE-LEVEL STUDENT WORK SAMPLES

To clarify how discussion posts were classified, representative examples of stage-level behaviors are summarized below. The wording has been rewritten for clarity and conciseness while preserving the structure of the original student reasoning. Similar examples were later shared with students as instructional models to help them strengthen their discussion posts.

Stage 2 (Emerging User):

"I used Ohm's Law to calculate the current and applied Kirchhoff's Voltage Law to check the voltage drops. Then I asked AI to confirm my final answer. It matched."

Stage 3 (Developing User):

"I solved the series–parallel circuit by calculating equivalent resistance, branch currents, and voltage drops. I then checked my results with AI and confirmed them using Multisim measurements. All three approaches were consistent."

Stage 4 (Advancing User – Adversarial Questioning):

"I asked AI to find assumptions in my solution. It treated the source as ideal and assumed equal branch resistances. I tested that by changing one resistor value and re-checking the current division."

Stage 4 (Advancing User – Hallucination Detection):

"AI stated that the cutoff frequency formula included an additional term. Based on class discussion about common AI hallucinations, I rechecked the textbook and my notes and confirmed that the extra term was incorrect. I asked AI to justify its derivation, and it revised the explanation."

Stage 5 (Fluent User):

"I solved the problem manually, used AI to verify the steps, asked it to challenge my assumptions, requested a short quiz to test my understanding, and explored how the circuit behavior changes if resistance doubles."

Stage 5 (Fluent User – High-Pass Filter with Hallucination Detection):

"I calculated the cutoff frequency of the high-pass RC filter manually using $f_c=1/2\pi RC$ and then asked AI to verify my result. AI provided a different expression that included an additional gain factor. Based on class discussion about possible AI hallucinations, I checked my textbook and confirmed that the extra term was incorrect for a simple passive filter. I asked AI to explain the discrepancy, and it corrected the formula. I then used Multisim to validate the cutoff frequency and asked AI how the cutoff would shift if capacitance were reduced by half. Finally, I requested a short quiz to confirm my understanding of high-pass filter behavior."

Posts were classified based on observable prompting behaviors and integration of multiple AI roles, consistent with the coding rubric in ***Appendix B***.

SECTION A GROWTH

Following the appearance of early advanced peer examples in Week 4, Section A demonstrated a consistent increase in higher-stage behaviors. This growth was observable in successive weekly cohorts of discussion posts, with Stage 3 behaviors becoming more common in Weeks 5-6 before Stage 4-5 integration became prevalent in Weeks 7-8. These included:

- Multi-method verification (manual, AI, and simulation comparison)
- Adversarial questioning of AI outputs
- Reverse prompting to test understanding
- Exploratory design variations beyond assignment requirements

By Weeks 7–8, a small subset of students demonstrated full Stage 5 integration, combining multiple AI roles within a single reasoning process.

SECTION B LIMITED GROWTH

In contrast, Section B participants largely remained at Stage 2, using AI primarily for explanation and answer confirmation. By Weeks 7–8, 4% of Section B posts were classified as Stage 4–5. Across the course, these advanced behaviors were produced by only two students, both of whom demonstrated Stage 4 behaviors; no Section B student demonstrated Stage 5 integration.

SUMMARY OF KEY FINDINGS

Taken together, the results show a clear divergence in AI fluency development between the two sections despite identical instruction. Section A demonstrated substantial adoption of advanced reasoning behaviors after early peer examples appeared, while Section B showed minimal movement beyond answer checking. The timing of peer examples was associated with the observed divergence; however, the large difference in full-time employment, available study time, and other unmeasured student or section characteristics provide plausible alternative or interacting explanations. The Discussion therefore interprets peer modeling as one associated factor rather than as a causal mechanism.

DISCUSSION

The two course sections developed noticeably different patterns of AI use even though they followed the same instructional structure. Section A showed steady growth in advanced AI reasoning behaviors, while Section B remained mostly at basic answer-checking. To better understand this difference, we examined how peer modeling and available time appear to have worked together to support adoption of advanced AI roles.

PEER EXAMPLES AND OBSERVED FLUENCY DEVELOPMENT

Peer examples were temporally associated with Section A's progression. Engineering problem-solving requires students to state assumptions, verify results using multiple methods, and work within defined constraints. When students saw classmates using AI to support these steps, they could see how the framework applied to

real assignments. This observation is consistent with peer modeling, but the study design does not isolate peer effects from other section-level differences.

Social learning theory establishes that observational learning and modeling can shape the acquisition of behavior (Bandura, 1977). In this study, peer discussion posts and laboratory artifacts made complete reasoning sequences visible to classmates, including manual calculations, simulation checks, and challenges to AI-generated assumptions. This provides a theoretically plausible basis for interpreting peer examples as one influence on students' adoption of advanced AI behaviors, while not establishing causation.

Diffusion-of-innovation theory identifies perceived relative advantage and compatibility with existing practices as factors associated with adoption (Rogers, 2003). In this study, the first Stage 4–5 artifacts in Section A provided assignment-specific examples of how the AI roles could be incorporated into circuit analysis. Increased use of advanced AI behaviors was subsequently observed among a larger portion of students; this temporal sequence is associative rather than causal.

The framework also reinforces standard engineering habits. By requiring multi-method verification and encouraging students to question AI outputs, it promotes the same disciplined checking process engineers use in professional practice.

PEER MODELING, EMPLOYMENT STATUS, AND TIME CONSTRAINTS

In Section A, the first advanced artifacts appeared in Week 4. After that point, higher-level AI behaviors increased steadily. Section B did not produce similar early advanced examples.

Voluntary self-reports showed that about 68% of students in Section B were working full-time, compared with 22% in Section A. Students in Section B often mentioned time pressure and the need to complete assignments efficiently.

Peer modeling, employment status, and available time may have interacted. Seeing strong examples can make advanced AI strategies more visible, while students also need sufficient time to read peer work, test similar prompts, and revise their reasoning. The substantially higher proportion of full-time workers in Section B therefore represents a major competing explanation for the observed section-level difference. Other unmeasured factors, including prior preparation, motivation, digital literacy, study habits, and informal peer interaction, may also have contributed.

Although performance differences were observed between sections, this study was not designed to determine whether AI fluency directly caused improved learning outcomes. The results are descriptive. Future research should examine whether movement through AI fluency stages is associated with measurable gains in engineering understanding under controlled conditions

INSTRUCTOR DEMONSTRATION AND PEER EXAMPLES

The instructor demonstrated all four AI roles during Week 1. Advanced behaviors were not commonly observed until later, when peer-produced examples appeared in Section A. This sequence suggests that assignment-specific peer examples may have complemented the initial instructor demonstration, although the observational design does not permit attribution of the later changes to peer modeling alone.

Cognitive apprenticeship emphasizes making otherwise tacit cognitive processes visible through modeling, coaching, guided practice, and reflection (Collins et al., 1989). Dialogic approaches likewise emphasize learning through interaction with ideas and perspectives (Wegerif, 2007). Together, these perspectives provide a theoretical basis for interpreting why assignment-specific peer artifacts may have made the AI framework more concrete and usable for students. They do not, however, establish that peer examples caused the section-level differences observed in this study.

In this case, peer artifacts made the framework concrete and assignment specific. Their appearance coincided with subsequent changes in Section A, but differences in employment status, available time, and other unmeasured section characteristics prevent a causal interpretation.

A recurring question is whether increased AI fluency leads to improved learning outcomes. While this is an important consideration, it was intentionally outside the scope of the present study. This work focuses on establishing a behavioral framework and documenting patterns of AI use as they emerge in authentic coursework. Future research will examine whether progression through AI fluency stages is associated with measurable gains in engineering performance, particularly in tasks involving verification, design iteration, and assumption testing.

INSTRUCTIONAL IMPLICATIONS

These findings suggest several practical strategies for supporting AI fluency and accelerating early peer modeling.

- **Make advanced reasoning visible early. In the first two weeks, share anonymized Stage 4–5 examples or highlight strong student posts so learners can clearly see what advanced AI reasoning looks like. Early visibility may reduce ambiguity and support earlier adoption.**
- **Structure verification into assignments.** Rather than presenting advanced AI roles as optional strategies, embed them directly into required tasks and grading criteria. For example, require students to verify results using multiple methods or identify assumptions in their solutions.
- **Provide guided support tools.** Offer role-based prompt templates that help students compare methods, test assumptions, and verify results without additional cognitive overhead.
- **Actively seed peer diffusion.** Instructors can amplify strong behaviors rather than waiting for them to emerge organically. Practical approaches include:
  - Sharing two to three anonymized Stage 4–5 examples in Week 1 with brief annotations.
  - Publicly spotlighting strong Stage 3+ behaviors in Weeks 2–3.
  - Assigning structured peer review in Week 2, asking students to identify the most thorough verification strategy.
  - Designing Week 3–4 prompts that explicitly require multi-step verification.

In this study, both sections operated under the same course design and workload. Advanced AI use did not require additional assignments. Several full-time working students progressed to advanced stages when they connected AI use to professional problem-solving. This observation suggests that perceived relevance may also matter, but the present study cannot determine the relative contribution of relevance, time availability, peer modeling, or other student characteristics

SUPPORTING TIME-CONSTRAINED LEARNERS

For students with limited discretionary time—such as full-time workers or caregivers—advanced AI roles should be positioned as efficiency tools rather than additional requirements. Design adjustments that support this population include:

- Frame roles as time-saving strategies. Emphasize that verification and adversarial questioning reduce rework and prevent downstream errors.
- Provide prompt templates. Offer copy-ready examples so students do not need to construct prompts from scratch.
- Use micro-modeling. Short demonstration clips (30–60 seconds) showing a single AI role in action provide accessible examples without requiring extended study time.
- Highlight professional relevance. Explicitly connect AI fluency to workplace problem-solving, particularly for working adults who may adopt advanced roles when they see alignment with professional practice.

These adjustments reinforce disciplined AI use while respecting time constraints.

LIMITATIONS

This study was conducted within a single course, taught by one instructor, in an online eight-week format. As such, the findings reflect a specific instructional context and student population and may not generalize to all engineering settings.

The analysis relied on student-generated artifacts (discussion posts and laboratory reports), along with instructor memos and student emails. These sources capture only AI use that students explicitly documented or chose to share and may underrepresent informal or unreported interactions.

Although the coding rubric was applied systematically across artifacts, classification was conducted by a single instructor-researcher. A subset of artifacts was reviewed a second time after an interval to support consistency of interpretation. Future studies incorporating multiple coders and formal inter-rater reliability measures would strengthen methodological rigor.

Because this was an observational and reflective analysis rather than a controlled experimental design, the study cannot establish causal relationships among peer modeling, AI engagement, and learning outcomes. Observed differences between sections may reflect pre-existing differences in employment status, available study time, prior technical preparation, digital literacy, motivation, study habits, informal peer interaction, or other uncontrolled characteristics.

DEMOGRAPHIC AND CONTEXTUAL CONSTRAINTS

A notable limitation is the substantial difference in full-time employment between the two sections. Employment status was determined from voluntary self-reports provided during first-week introductions rather than from a structured demographic survey. Approximately 22% of Section A and 68% of Section B reported full-time employment. This difference is a major potential confound because employment-related time demands and cognitive load may have influenced both the production of advanced peer examples and students' ability to engage with them.

No other demographic variables were systematically collected. Factors such as age, prior technical experience, academic standing within the first year, or other personal circumstances may have influenced peer interaction patterns and AI fluency development but were not examined. These represent important directions for future research.

Both sections were delivered fully online, as this program offers no onsite alternative. Physical classroom interaction was therefore not a source of difference between sections; however, informal collaboration outside the course platform was not measured. External obligations beyond employment—such as family responsibilities, caregiving duties, or workplace technology constraints—were also not systematically collected.

Alternative explanations—including informal peer collaboration outside the course platform, workplace restrictions on AI tool access, prior technical preparation, digital literacy, student motivation, study habits, and section-level interaction dynamics—remain plausible but untested within the present design.

The analysis reports aggregate stage proportions and milestone observations rather than a complete numerical distribution for every week. This limits quantitative granularity and the extent to which week-to-week changes can be independently compared.

Finally, because only documented AI interactions were examined, the study may not fully represent the breadth of students' AI use outside formal coursework. Future research incorporating interviews, recordings of real-time AI use, or controlled interventions could further clarify the mechanisms underlying AI fluency development and validate the framework across diverse populations.

FUTURE DIRECTIONS

This study is an early step in understanding how students adopt structured AI roles in a first-year engineering course. The broader goal is not simply to increase AI use, but to help students use AI in ways that support sound engineering reasoning and responsible professional practice.

Future work will focus on developing clear guidelines for faculty who want to implement the AI fluency framework in their own courses. This includes identifying where AI tools best support learning, where instructor oversight remains essential, and how to help students recognize common AI limitations such as incorrect formulas, incomplete reasoning, or fabricated references.

Ongoing work will also explore applying the framework beyond electronics to other engineering disciplines such as mechanics, thermodynamics, and circuits at higher levels. The goal is to develop a practical implementation model that other instructors can adapt without starting from scratch.

Finally, future validation studies should examine whether students who reach higher AI fluency stages perform better on specific engineering tasks—particularly those involving multi-method verification, design iteration, and assumption testing. Until that evidence exists, the present findings should be understood as a foundation for that next step rather than proof that AI fluency improves engineering learning outcomes.

CONCLUSION

This study provides descriptive evidence of more advanced AI reasoning behaviors in a course section where structured guidance was accompanied by visible peer examples. Although both sections followed the same instructional design, the sections also differed substantially in full-time employment and therefore in likely time demands. The observed divergence should consequently be interpreted as an association among peer visibility, student context, and AI fluency progression rather than as evidence of a causal peer-modeling effect.

The contrasting trajectories suggest that peer visibility, discretionary time, perceived relevance, and other student or section characteristics may influence the adoption of more advanced AI practices. The observational design does not permit their independent effects to be determined.

The AI fluency framework introduced in this study offers a structured, role-based approach for using AI to support verification, exploration, and reasoning beyond answer checking. The findings support practical consideration of early exemplars and structured AI roles in course design, while not establishing that these strategies cause higher AI fluency or improved learning outcomes. No direct measures of student performance were analyzed in this study.

Although derived from a single course context, this work contributes a practical model of how AI fluency progression can unfold in authentic engineering classrooms. It provides a foundation for future research examining how course design, student characteristics, and time constraints influence effective AI use in engineering education.

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APPENDIX A: STUDENT PROGRESSION EXAMPLES

This appendix provides two real examples (pseudonyms used) showing how students progressed through the AI fluency stages.

MARIA'S PATH FROM LIMITED TIME TO STAGE 5 FLUENCY

Maria, a student in Section B, worked full-time as a semiconductor technician (45+ hours per week). Early in the term, she used AI primarily for confirmation checks and clarification of final answers. Her discussion posts reflected Stage 2 behavior, with limited experimentation beyond basic verification.

In Week 5, during the module on transistor biasing, Maria encountered difficulty calculating base current, collector current, and voltage drops across the collector and emitter resistors. She initially used AI to confirm her manual calculations using Kirchhoff's Voltage Law and the transistor current relationship ($I_C = \beta I_B$). After receiving instructor feedback encouraging deeper engagement, she began asking AI to explain the assumptions behind using a fixed β value and ideal supply conditions. She compared these explanations with her Multisim simulation results and documented small differences in collector voltage caused by model assumptions. This shift marked her transition into Stage 3–4 behaviors, as she moved from simple confirmation to analytical comparison and assumption awareness.

By Week 7, during the filter design module, Maria demonstrated full Stage 5 (Fluent User) behaviors:

- Multi-method verification (manual calculation, AI cross-checking, simulation validation)
- Adversarial questioning (asking AI to identify hidden assumptions and edge cases)
- Reverse prompting (requesting AI to test her conceptual understanding before posting)
- Exploratory variations beyond assignment requirements

In Week 8, Maria reflected that earlier exposure to peer examples of advanced AI use might have helped her engage more deeply sooner. While this does not establish causation, it suggests that both time constraints and visibility of peer practices may influence the pace at which students adopt more sophisticated AI strategies.

ALEX'S PROGRESSION FROM STAGE 2 TO STAGE 5

Alex, a student in Section A, progressed steadily in his use of AI across the session. In Week 2 topic on series circuits, he confirmed his solution using AI, demonstrating Stage 2 (Emerging User) behavior. The instructor encouraged him to check methods and try deeper questioning.

In Week 5, during the module on diodes and basic transistor operation, Alex demonstrated Stage 3 (Developing User) behaviors. While analyzing a diode biasing problem, he calculated the diode current manually using Ohm's Law and the assumed 0.7V forward drop model. He then asked AI to explain the assumptions behind the constant-voltage model and compared that explanation to his Multisim simulation results. He noted small differences between idealized calculations and simulated behavior and reflected on why those differences occurred.

By Week 7, while working on low-pass filters, Alex demonstrated full Stage 5 (Fluent User) behavior in the following ways:

- Manual calculation
- AI verification (Foil)
- Simulation
- Asking AI to identify assumptions
- Asking AI to quiz him (Interrogator)
- Exploring alternate designs (Catalyst)

Alex's discussion posts met Stage 5 criteria according to the coding rubric.

APPENDIX B:

AI FLUENCY CODING RUBRIC

The following rubric was used to classify student artifacts (discussion posts and laboratory reports) into progressive stages of AI fluency. Stages reflect observable behaviors rather than self-reported intent.

Stage 1: Non-User
- No evidence of AI use
- Problem-solving documented using traditional methods only
- No reference to AI interaction, verification, or AI-supported reasoning

Stage 2: Emerging User
- AI used primarily for explanations or answer confirmation
- AI interaction limited to checking a final answer
- No evidence of comparison, verification, or critical engagement

Example indicators:
- "ChatGPT gave the same answer"
- "I asked AI to explain the formula"

Stage 3: Developing User
- Student verifies a solution using two or more methods (e.g., manual calculation, AI output, simulation)
- Explicit comparison of results across methods
- Documentation of reasoning beyond answer confirmation

Example indicators:
- Manual calculation followed by AI check
- Simulation used to confirm theoretical result
- Explicit statement of agreement or discrepancy between methods

Stage 4: Advancing User
- Student challenges AI reasoning or identifies inaccuracies
- Use of adversarial questioning
- Investigation of discrepancies
- Discussion of assumptions

Example indicators:
- "AI said the current divides equally, but that only happens if the resistors are equal. What if one branch has twice the resistance?"
- "AI said −3 dB is half voltage; that's incorrect—it's 0.707 of input"

Stage 5: Fluent User
- Integration of multiple AI roles within a single problem-solving episode
- Evidence of verification, exploration, adversarial questioning, and reverse prompting
- Explicit metacognitive reflection on what was learned through AI interaction
- Clear articulation of reasoning progression

Example indicators:
- Multi-method verification (manual + AI + simulation)
- Reverse prompting used for self-testing
- AI assumptions questioned and refined
- Exploration of boundary conditions or design variations

CODING APPROACH

Each student artifact was evaluated independently and assigned a single stage based on the highest level of fluency demonstrated within that artifact.

Because students submitted multiple artifacts during the term, individual students could appear at different stages over time, allowing observation of progression.

To support consistency in interpretation, a subset of artifacts was reviewed a second time after an interval and compared with the original classifications. Stage assignments were largely consistent, indicating stable application of the rubric.

When an artifact demonstrated features spanning multiple stages, classification defaulted to the lower stage unless multiple clear indicators of higher-level engagement were present.

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Structured Human–AI Collaboration in the Classroom: A Pilot Assessment of AI Literacy Performance in Undergraduate Technology Courses

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ABSTRACT

This pilot study reports the implementation and preliminary assessment of a structured seven-stage instructional framework for developing responsible artificial intelligence (AI) literacy in undergraduate technology courses. The framework was implemented sequentially during the January, March, and June 2026 instructional sessions at DeVry University. It positions AI as a collaborative learning partner and integrates prompting instruction, guided practice, critical evaluation, information verification, academic integrity, reflection, and career-readiness connections. A 10-item pre- and post-assessment measured seven proposed categories of AI literacy. The January 2026 respondent groups showed an increase in mean performance from 52% (SD = 41%, n = 11) to 96% (SD = 5%, n = 5). The March 2026 groups showed a decrease from 86% (SD = 17%, n = 5) to 70% (SD = 14%, n = 5), while the June 2026 groups increased from 88% (SD = 5%, n = 8) to 93% (SD = 8%, n = 7). Post-assessment item accuracy was highest for appropriate AI use, critical evaluation, and responsibility and accountability. The single item mapped to metacognitive awareness showed the lowest accuracy, identifying a question for further instructional and measurement research rather than establishing a construct-level weakness. These preliminary findings establish the framework's viability across varied baseline conditions and launch a clearly defined program of research, with the next phase targeting matched participant designs, validated multidimensional instruments, comparison conditions, and longitudinal assessment.

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INTRODUCTION

The rapid integration of artificial intelligence (AI) into academic and professional environments presents both opportunities and challenges for higher education. While AI tools can enhance learning by providing explanations, generating ideas, and supporting problem-solving, their misuse can undermine critical thinking, academic integrity, and long-term skill development.

A key challenge for educators is ensuring that students use AI in ways that strengthen, rather than replace, their cognitive processes. Without structured guidance, students may over-rely on AI-generated outputs, fail to verify information, or misunderstand their responsibility for submitted work. These behaviors can lead to shallow learning and reduced preparedness for professional environments where judgment and accountability are essential. This paper argues that a structured, sequenced instructional framework — one that integrates prompting instruction, guided AI use, critical evaluation, verification, academic integrity, reflection, and career-readiness connections — is both a practical and theoretically grounded response to this challenge, and that implementing such a framework in undergraduate technology courses produces promising early evidence of improved AI literacy performance.

Addressing these challenges requires both a clear definition of AI literacy and evidence of how to teach it. The following section reviews current scholarship on AI literacy and related pedagogy before presenting the conceptual framework and study design.

AI LITERACY, PEDAGOGY, AND ETHICAL USE

AI literacy is increasingly understood as a multidimensional capacity rather than simple familiarity with AI tools. Long and Magerko (2020) identify competencies that include recognizing AI capabilities and limitations, critically evaluating AI output, and understanding social implications. Ng et al. (2021) similarly organize AI literacy around knowing and understanding AI, using and applying it, evaluating and creating with it, and addressing ethical concerns. Southworth et al. (2023) extend this work to curriculum-level implementation, arguing that responsible AI use must be intentionally developed across disciplines. Recent measurement research reinforces both the importance, and the emerging status, of the construct. Lintner's (2024) systematic review found broad agreement that technical understanding, societal impact, and ethics are central to AI literacy, but also found that existing measures vary in how they treat higher-order evaluation and have limited evidence for responsiveness, cross-cultural validity, and measurement error. These findings support multidimensional instruction while underscoring the need for cautious interpretation and stronger instrument validation in pilot research.

Research on AI pedagogy further suggests that learning outcomes depend on how generative AI is incorporated into instructional activity. AI can provide feedback, explanations, and opportunities for iterative practice, but unstructured use can encourage overreliance on AI or substitution of AI output for student reasoning. In a higher education case study, Tzirides et al. (2024) demonstrated the value of combining human and artificial intelligence through pedagogical processes that require learners to interpret and critically assess AI contributions. Chan's (2023) AI Ecological Education Policy Framework likewise connects pedagogical use with governance, accountability, training, and ethical responsibility. Together, this literature supports instructional designs that retain human agency and require students to question, verify, and improve AI-generated material rather than accept it automatically.

Ethical AI literacy is therefore not separate from effective AI use. It includes attention to reliability, bias, privacy, transparency, academic integrity, and responsibility for decisions or work produced with AI assistance. UNESCO's human-centered guidance emphasizes integrating generative AI through ethical validation and pedagogical design that preserve human agency and promote safe, equitable, and meaningful use (Miao & Holmes, 2023). This perspective aligns with the intervention's requirements that students verify

information, disclose appropriate use, and remain accountable for final academic work. Despite this growing consensus on what AI literacy requires and why it matters, fewer studies have documented a replicable, classroom-ready instructional sequence that operationalizes these principles within a single session — the gap this study addresses.

CONCEPTUAL FRAMEWORK

Kolb's (2015) experiential learning theory provides the primary conceptual foundation for the intervention. The seven-stage framework operationalizes the four processes of experiential learning across a structured AI-supported activity. Students obtain concrete experience by interacting with AI in an authentic career-based scenario. Critical review and reflection support reflective observation by requiring students to identify useful, unclear, or inaccurate elements of AI-generated output. Framing, prompting instruction, and the career-readiness debrief support abstract conceptualization by helping students formulate general principles for effective and responsible AI use. Iterative prompting, verification, and revision provide opportunities for active experimentation. The seven stages are not intended as a one-to-one or strictly linear reproduction of Kolb's cycle; rather, they translate its interconnected learning processes into a practical framework for AI literacy instruction.

Kuh and O'Donnell's (2013) account of high-impact educational practices provides a complementary pedagogical rationale. The framework asks students to invest effort in an authentic problem, interact with substantive feedback, reflect on their decisions, and connect the activity to professional responsibilities. These features informed the design of the guided scenarios, structured review questions, and career-readiness debrief.

STUDY PURPOSE AND CONTRIBUTION

Existing scholarship establishes the need for critical, ethical, and human-centered AI literacy, but fewer studies document a replicable instructional sequence that integrates prompting, authentic AI use, critical review, verification, reflection, and career relevance within one classroom framework. This pilot study addresses that gap by documenting a structured seven-stage model and reporting preliminary benchmark patterns across three implementations. It has two purposes: to provide a practical framework for classroom adaptation and to generate evidence and methodological priorities for subsequent, more rigorous research. Specifically, the study asks: What descriptive differences in pre- and post-assessment performance are observed across three undergraduate course sessions following participation in the structured AI literacy intervention?

The intervention is distinguished by the deliberate sequencing of complementary elements within one classroom experience. The seven stages combine baseline assessment, pedagogical framing, prompting instruction, authentic career-based application with explicit integrity expectations, critical review and verification, reflection, and a career-readiness debrief followed by post-assessment. This integrated sequence moves students beyond generating AI output toward evaluating, revising, verifying, and assuming responsibility for that output. The framework's contribution therefore lies in connecting operational, critical, ethical, reflective, and professional dimensions of AI literacy within a replicable instructional process.

ETHICAL APPROVAL

This study involved analyzing voluntarily submitted, de-identified student assessment responses collected as part of routine instructional activity. In accordance with DeVry University's research policy, the study was reviewed and determined to qualify for exemption from full IRB review under the category of normal educational practices (IRB Exemption Category 1). Student participation in both the pre- and post-assessments was voluntary, and no personally identifiable information was retained in the dataset used for analysis.

GENERATIVE AI USE DISCLOSURE

In accordance with emerging scholarly norms and DUJOSR disclosure expectations, the authors acknowledge that generative AI tools were used during the preparation of this manuscript. Specifically, AI assistance was used to support drafting, editing, structural revision, and consistency review of the manuscript text. All content, arguments, data, interpretations, and conclusions are the intellectual work of the authors. The authors take full responsibility for the accuracy, integrity, and scholarly merit of the published work. The instructional framework, assessment instrument, and data reported in this study were developed and collected independently of any AI tool.

METHODOLOGY

RESEARCH DESIGN

This pilot study used pre- and post-intervention assessments administered within three instructional sessions to examine patterns in student AI literacy assessment performance. Participant-level responses could not be consistently linked across administrations; therefore, the primary analysis compares group-level descriptive statistics rather than individual learning gains. Differences between pre- and post-assessment means represent changes in respondent-group performance and should not be interpreted as within-student change or as causal effects of the intervention. Given the small samples, incomplete matching, and differences between assessment forms, all analyses are descriptive and preliminary.

Table 1 - Participant Flow by Instructional Session

SESSION	PRE RESPONSES	POST RESPONSES	COUNT DIFFERENCE	POST/PRE RATIO
January 2026	11	5	−6	45.5%
March 2026	5	5	0	100.0%
June 2026	8	7	−1	87.5%
Total	24	17	−7	70.8%

Note: *The post/pre ratio compares response counts only. Because responses were not fully matched, it should not be interpreted as participant-level retention.*

PARTICIPANTS

Participants were undergraduate students enrolled in technology-related courses at DeVry University. The intervention was implemented sequentially across three instructional sessions: January, March, and June 2026.

- January 2026 session: 11 pre-assessment responses, 5 post-assessment responses
- March 2026 session: 5 pre-assessment responses, 5 post-assessment responses
- June 2026 session: 8 pre-assessment responses, 7 post-assessment responses

Participation in both assessments was voluntary, and post-assessment completion varied by session. Equal counts in March do not, by themselves, confirm that the same individuals completed both assessments. No consistently available participant identifier permitted complete matching across administrations (see ***Table 1***).

PARTICIPANT ATTRITION AND ANALYTIC IMPLICATIONS

The difference between pre- and post-assessment counts was most pronounced in January, for which the post-assessment response rate was 45.5%. The corresponding rates were 100.0% in March and 87.5% in June. Differential participation may have introduced attrition bias, particularly in January, where only n = 5 of 11 pre-assessment respondents completed the post-assessment. Students who completed the post-assessment may have differed from noncompleters in engagement,

attendance, motivation, prior AI experience, or academic performance. Consequently, observed differences between pre- and post-assessment group means may reflect both intervention-associated patterns and changes in respondent composition rather than individual learning gains..

INSTRUMENT

A 10-item assessment instrument was developed to provide a brief diagnostic of student AI literacy across seven proposed conceptual categories. ***Table 2*** presents each item, its primary mapped category, and a brief item summary.

The instrument used scenario-based multiple-choice questions to assess applied reasoning and reduce guessing. Each item was scored as correct (1 point) or incorrect (0 points), yielding a total score out of 10. Item difficulty ratings, as reported by the quiz platform, ranged from 1 (easy) to 7 (hard).

Item coverage was uneven across the proposed categories. Appropriate AI Use, Critical Evaluation of AI Output, and Responsibility and Accountability were each represented by two items. Verification and Source Validation, Ethical Use and Academic Integrity, Metacognitive Awareness, and Career and Workforce Readiness were each represented by one item. The instrument was designed as a brief pilot diagnostic; Table 2 shows coverage and item counts for each category.

Table 2 - Assessment Item-to-Category Mapping

ITEM	MAPPED AI LITERACY CATEGORY	ITEM SUMMARY
Q1	Appropriate AI Use	Main goal of using AI in this activity
Q2	Appropriate AI Use	Example of appropriate AI use in this activity
Q3	Critical Evaluation of AI Output	Why are students asked to critically review AI responses?
Q8	Critical Evaluation of AI Output	Which action BEST demonstrates critical evaluation of AI output?
Q9	Verification and Source Validation	AI gives a confident answer contradicting the textbook – most responsible action?
Q6	Ethical Use and Academic Integrity	Which statement BEST describes appropriate AI use in coursework?
Q4	Responsibility and Accountability	Which action demonstrates responsible and ethical AI use?

ITEM	MAPPED AI LITERACY CATEGORY	ITEM SUMMARY
Q5	Responsibility and Accountability	Who is responsible for the final content when AI is used?
Q7	Metacognitive Awareness	Why was the student's own paragraph required in Step 1?
Q10	Career and Workforce Readiness	How does responsible AI use support long-term career readiness?

Note: *Four categories are represented by one item. Mappings identify the primary concept addressed by each question and do not constitute validated subscales or comprehensive measures of the corresponding constructs.*

PROCEDURE

The instructional intervention was delivered via a structured slide presentation and followed a seven-stage sequence designed to move students progressively from orientation through guided practice to reflective assessment. Each stage is described below.

Stage 1: Pre-Assessment. Before any instruction began, students completed a 10-item pre-assessment via SurveyMonkey (unique links were used for each session). The pre-assessment was framed explicitly as a baseline measure: "This helps us understand your current perspective on AI before starting the activity." Students were not coached or primed before completing it, ensuring scores reflected genuine prior knowledge.

Stage 2: Framing — Why Use AI in Learning? A brief framing slide established the pedagogical rationale for the activity before any AI use began. Students were told that AI supports thinking and problem-solving, builds career-relevant digital skills, and encourages critical evaluation rather than shortcuts. This framing positioned AI as a cognitive tool rather than a shortcut, setting expectations for the responsible use that the rest of the activity reinforced.

Stage 3: Prompting Instruction ("Prompting 101"). A dedicated instructional module introduced students to four categories of AI prompting: (1) instruction-based prompts, which specify task, audience, format, and constraints; (2) role-based prompts, which assign the AI a persona or area of expertise to shape its response; (3) example-based (few-shot) prompts, which provide a sample output for the AI to match in style or format; and (4) iterative prompts, which refine an initial response through successive follow-up instructions. For each category, students were shown side-by-side examples of weak and strong prompts. For instance, the weak prompt "Explain mitosis" was contrasted with the strong version: "Explain mitosis in 3 bullet points, comparing it to meiosis, for a high school audience." This module ensured that students entered the guided activity with a shared, concrete vocabulary for interacting with AI tools.

Stage 4: Guided AI Activity. Students selected one of four career-contextualized scenarios and used an AI tool to complete it:

- Scenario 1 (IoT): As an IT professional exploring connected systems, use AI to brainstorm three essay ideas on the Internet of Things, with an emphasis on practical use cases and real-world impacts.
- Scenario 2 (AI Communication): As an IT professional responsible for introducing emerging technologies to non-technical users, use AI to help explain AI concepts in clear and understandable language.
- Scenario 3 (Network Security): As a security professional responsible for protecting an organization's network, consult AI to generate actionable ideas for improving network security and minimizing vulnerabilities.
- Scenario 4 (Writing Feedback): As a student seeking feedback on a written paragraph, use AI to provide suggestions for improving clarity, flow, and the strength of the argument.

Each scenario was framed in a professional role to reinforce the career-readiness category of AI literacy and to provide an authentic context for evaluating AI output. Before students began, an Academic Integrity slide made explicit the expectations around responsible use and personal accountability for submitted work.

Stage 5: Critical Review and Verification. Following the AI activity, students were guided through a structured critical review using four reflective prompts: "What was helpful?" "What was unclear or inaccurate?" "What did YOU improve?" and "Would you trust it academically?" The explicit framing was: "This step is about evaluating the AI's response, not accepting it automatically." This stage directly targeted the Verification and Source Validation and Critical Evaluation categories measured in the assessment instrument.

Stage 6: Reflection. Students were invited to reflect on how AI had supported their learning while keeping them in control of their work. Oral sharing via microphone was offered as an optional format, allowing students to articulate their metacognitive awareness in their own words. This stage maps onto the reflective observation phase of Kolb's (2015) experiential learning cycle and was designed to consolidate the cognitive shift from passive AI use to active, accountable partnership.

Stage 7: Career-Ready Skills Debrief and Post-Assessment. A closing slide explicitly named the transferable skills students practiced—critical thinking, ethical use of technology, and clear communication—and connected them to employer expectations. Students then completed the post-assessment via a separate SurveyMonkey link. Because distinct links were used across administrations and formal equivalence testing was not conducted, differences in wording or framing between forms may have influenced performance comparisons. This issue is addressed in the From Pilot to Program: Next Steps section.

DATA ANALYSIS

Assessment responses were summarized by session and administration using sample size, mean, standard deviation, minimum, median, and maximum. For each session, we calculated the post-assessment group mean minus the pre-assessment group mean as a descriptive difference in group means. These differences are reported in percentage points and are not individual change scores because responses were not fully matched. Category-level percentages in ***Table 3*** describe accuracy on the items mapped to each category; they are not validated subscale scores.

No inferential tests were conducted. The small session-level samples, incomplete participant matching, and unvalidated equivalence of the assessment forms would make statistical significance tests difficult to interpret and potentially misleading. The cohorts were analyzed separately rather than pooled because baseline performance varied substantially, assessment forms were not formally established as equivalent, and response matching was incomplete.

Table 3 - Post-Assessment Accuracy for Items Mapped to AI Literacy Categories

MAPPED AI LITERACY CATEGORY	JANUARY POST (%)	JUNE POST (%)
Appropriate AI Use (Q1–Q2)	100	100
Critical Evaluation of AI Output (Q3, Q8)	100	100
Verification & Source Validation (Q9)	80	100
Ethical Use & Academic Integrity (Q6)	100	86
Responsibility & Accountability (Q4–Q5)	100	100

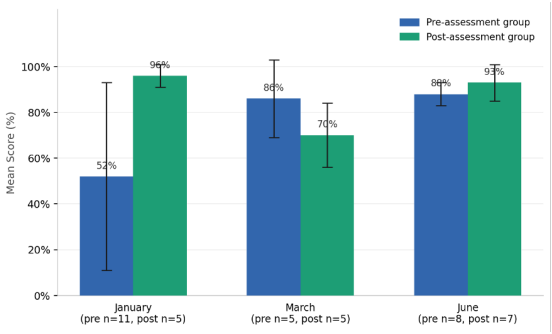
MAPPED AI LITERACY CATEGORY	JANUARY POST (%)	JUNE POST (%)
Metacognitive Awareness (Q7)	80	57
Career & Workforce Readiness (Q10)	100	86

Note: *Percentages describe item accuracy for the January (n = 5) and June (n = 7) post-assessment respondent groups, not validated category scores. Categories represented by one item should be interpreted cautiously.*

RESULTS

Table 4 summarizes descriptive statistics for pre- and post-assessment respondent groups across the three instructional sessions. Group means differed by +44 percentage points in January, −16 percentage points in March, and +5 percentage points in June. Because responses were not fully matched, these values describe differences between respondent groups and do not represent average within-student change. Two sessions (January and June) showed higher post-assessment group means; one session (March) showed a lower post-assessment group mean, interpreted primarily as a methodological caution regarding instrument equivalence and small-sample variability rather than as evidence against the intervention's effectiveness.

Figure 1 - Descriptive Pre- and Post-Assessment Respondent-Group Means by Session



Note: *Error bars represent ±1 SD. January: pre n = 11, post n = 5; March: pre n = 5, post n = 5; June: pre n = 8, post n = 7. Responses were not fully matched.*

JANUARY 2026 SESSION

The January session produced the largest difference between pre- and post-assessment group means. The pre-assessment respondent group had a mean of 52% (SD = 41%), with scores ranging from 0% to 100%. This wide spread indicates substantial heterogeneity in students' prior AI literacy. The post-assessment respondent group had a mean of 96% (SD = 5%), with scores ranging from 90% to 100%. The reduction in variability is consistent with greater convergence in assessment performance following the intervention.

January also experienced the greatest attrition: only n = 5 of 11 pre-assessment respondents completed the post-assessment. Without

Table 4 - Respondent-Group Descriptive Statistics by Session and Assessment Administration

SESSION	RESPONDENT GROUP	N	MEAN (%)	SD (%)	MIN (%)	MEDIAN (%)	MAX (%)
January 2026	Pre	11	52	41	0	80	100
January 2026	Post	5	96	5	90	100	100
March 2026	Pre	5	86	17	60	90	100
March 2026	Post	5	70	14	60	70	80
June 2026	Pre	8	88	5	80	90	90
June 2026	Post	7	93	8	80	90	100

Note: *The post/pre ratio compares response counts only. Because responses were not fully matched, it should not be interpreted as participant-level retention.*

participant-level matching, the analysis cannot determine how much of the observed difference reflects individual learning and how much reflects changes in respondent composition. The January pattern is consistent with the interpretation that structured instruction supported AI literacy development; however, unmatched respondent groups and substantial attrition prevent a causal attribution.

MARCH 2026 SESSION

The March session produced a pattern that differed from January and June. The pre-assessment respondent group had a mean of 86% (SD = 17%), while the post-assessment respondent group had a mean of 70% (SD = 14%). Given the very small samples (n = 5 at each administration), the absence of confirmed participant matching, and confirmed differences between assessment forms, this pattern should be interpreted cautiously. The available design cannot determine whether it reflects learning, respondent composition, measurement differences, or random variation. The March results are treated primarily as a methodological caution for future study design.

JUNE 2026 SESSION

The June session produced a positive difference between respondent-group means despite a high baseline. The pre-assessment respondent group had a mean of 88% (SD = 5%), while the post-assessment respondent group had a mean of 93% (SD = 8%). The +5 percentage-point difference is likely constrained by a ceiling effect, given the narrow pre-assessment score range (80–90%). Because n = 7 of 8 pre-assessment respondents completed the post-assessment but responses were not fully matched, this pattern remains a group-level association rather than a direct estimate of individual improvement.

Item-level analysis showed high accuracy on most post-assessment questions. Seven of the ten June post-assessment questions achieved 100% accuracy. Accuracy was lower on questions mapped to Metacognitive Awareness, Ethical Use and Academic Integrity, and Career and Workforce Readiness. Because each of these categories was represented by one item, the pattern identifies specific questions for instructional and measurement follow-up rather than indicating weaker construct-level competence.

ITEM-LEVEL OBSERVATIONS

Table 4 summarizes post-assessment accuracy for items mapped to the seven AI literacy categories in the January and June respondent groups. This table excludes March post-assessment item-level data because confirmed assessment-form differences prevent meaningful comparison with the pre-assessment items.

Accuracy was highest for items mapped to Appropriate AI Use, Critical Evaluation of AI Output, and Responsibility and Accountability, with both cohorts achieving 100% on these categories. Items mapped to Verification and Source Validation, Ethical Use and Academic Integrity, and Career and Workforce Readiness also showed generally high accuracy. The single item mapped to Metacognitive Awareness produced the lowest accuracy across both cohorts (January: 80%; June: 57%). Because one binary item cannot adequately represent a broad construct, this result should be treated as a preliminary signal for instrument refinement and additional instructional attention rather than evidence that students had comparatively weak metacognitive awareness.

DISCUSSION

This pilot study makes three contributions to emerging work on AI literacy in higher education. First, it documents a practical seven-stage framework that instructors can adapt to integrate prompting, guided AI use, critical review, verification, reflection, academic integrity, and career readiness within a single classroom session. Second, it provides preliminary benchmark data from authentic undergraduate technology-course settings across three implementations. Third, it identifies the item mapped to metacognitive awareness as a specific priority for instrument refinement and hypothesis testing in future research.

The benchmark patterns were heterogeneous but informative. Post-assessment respondent groups had higher means in January and June,

while March had a lower post-assessment mean. As noted in the Results, the March pattern is treated as a methodological caution — attributable to confirmed form differences, small-sample variability, and the absence of participant-level matching — rather than as evidence against the framework's effectiveness. The January and June patterns, which arose from substantially different baseline conditions, provide stronger and more interpretable preliminary evidence.

THEORETICAL ALIGNMENT

The intervention's structure operationalizes Kolb's (2015) experiential learning processes. The guided AI scenario provides concrete experience; critical review and reflection support reflective observation; prompting instruction and the career-readiness debrief promote abstract conceptualization; and iterative prompting, verification, and revision support active experimentation. This mapping explains why the intervention combines direct AI use with deliberate evaluation and reflection. The assessment patterns align with this theoretical rationale, but the study design does not establish that any individual component or the full cycle produced the observed differences.

The intervention also reflects Kuh and O'Donnell's (2013) framework of high-impact educational practices. It required students to engage actively with AI-generated content, consider feedback through structured review and verification, and assume accountability for final outputs. The positive patterns observed in both January and June are consistent with Kuh and O'Donnell's (2013) research on students engaged in well-designed, structured learning experiences, though the present descriptive results cannot determine the independent or combined effects of the framework's components.

POTENTIAL INSTRUCTIONAL MECHANISMS

The theoretical frameworks above identify why the intervention was designed as it was; the following section considers which specific components are most likely to have shaped the observed patterns, while recognizing that the present study cannot isolate individual stage effects.

Each stage of the intervention addressed a distinct aspect of responsible AI literacy. Initial framing and academic-integrity guidance established clear expectations for responsible AI use, giving students an explicit standard against which to evaluate their own behavior. Prompting instruction equipped students with a concrete vocabulary and transferable strategies for interacting purposefully with AI tools. Career-based scenarios grounded the activity in professional authenticity, strengthening relevance and motivating meaningful engagement. The structured critical-review and verification questions required students to actively evaluate the reliability and usefulness of AI output rather than accepting it at face value. Reflection and the career-readiness debrief provided opportunities to consolidate learning and connect responsible AI practices to longer-term professional and academic contexts. These mechanisms are grounded in the intervention's design and theoretical framework; the study's scope does not permit isolating the contribution of any individual stage.

The strong alignment between instructional content and assessment items confirms that the framework delivered what it was designed to teach. Students were assessed on the principles they practiced, and the high accuracy rates across most categories reflect that the instructional sequence successfully conveyed those principles within a single session. Establishing this baseline alignment is the appropriate first step before extending research to delayed retention and transfer—both priorities for the next phase of investigation.

The item mapped to Metacognitive Awareness produced the lowest post-assessment accuracy across both cohorts (January: 80%; June: 57%), making it the clearest target for instructional development. This result points to a specific gap: students demonstrated strong understanding of what responsible AI use looks like in principle but showed comparatively less certainty about

why reflective practices — such as generating their own thinking before consulting AI — are integral to that responsible use. Addressing this gap directly in future iterations, through additional scenario-based practice and multi-item measurement, would strengthen both the instructional framework and the assessment instrument.

Taken together, these pilot findings provide promising early evidence that the structured seven-stage framework is worth investigating further. The specific next steps — matched participants, validated instruments, comparison conditions, delayed assessment, and expanded scope — are detailed in the following section.

FROM PILOT TO PROGRAM: NEXT STEPS

This pilot study was designed as a first step in a programmatic research agenda rather than a definitive test of effectiveness. Each design choice that constrained the current analysis directly informs and motivates the next phase of research. Together, these constraints define a clear, prioritized roadmap from the preliminary benchmarks established here toward a rigorous, multi-context evidence base for structured AI literacy education.

PARTICIPANT SAMPLES AND MATCHING

The three sessions produced small respondent groups (ranging from n = 5 to n = 11 at pre-assessment), and participant-level responses could not be consistently linked across administrations. The next phase of this research will introduce anonymous linking codes at the point of pre-assessment to enable matched change-score analyses, providing a direct measure of individual learning rather than group-level differences. Expanding implementation across additional course sections and institutions will produce the larger, more diverse samples needed to test the generalizability of these preliminary patterns.

ASSESSMENT INSTRUMENT

The 10-item pilot instrument provided a useful first diagnostic but covered the seven proposed AI literacy categories unevenly, with four categories represented by a single item each. The next version of the instrument will expand to at least three items per category, incorporate open-ended and scenario-based formats alongside multiple-choice items, and undergo content-validity review and cognitive interviewing before further deployment. This development will transform the instrument from a brief pilot diagnostic into a validated, multidimensional measure capable of supporting subscale analysis.

ASSESSMENT FORM EQUIVALENCE

Different SurveyMonkey links were used across administrations without formal equivalence testing, introducing a potential source of variation that most likely explains the anomalous March pattern. Future studies will use identical pre- and post-assessment forms or formally establish parallel-form equivalence before comparing across timepoints.

STUDY DESIGN

The current study measured immediate post-assessment performance within a single session and included no comparison group, no delayed retention measure, and no transfer assessment. The next phase will incorporate a delayed post-assessment administered two to four weeks after the intervention to evaluate retention, a transfer task using unfamiliar AI-use scenarios to assess generalizability, and a comparison condition to isolate the contribution of the structured framework relative to unstructured AI use.

COMPONENT ANALYSIS

The seven stages were implemented as one integrated package, and no process or implementation-fidelity measures were collected to establish how students engaged with each component. Future research will introduce stage-level fidelity checks and, where feasible, dismantling designs that vary individual components across conditions. This will allow the field to identify which elements of the framework are necessary, sufficient, or synergistic in producing AI literacy gains.

SCOPE AND CONTEXT

Participants were drawn exclusively from technology-related courses at a single institution. Planned replications will extend the framework to courses in business, health sciences, and the humanities, and will recruit participants across multiple institutions and demographic groups. Mixed-methods components — including student reflections, interviews, and focus groups — will be added to explain quantitative patterns, surface student perceptions of the framework's most valuable elements, and examine whether responsible AI-use principles transfer to subsequent academic tasks beyond the activity context.

CONCLUSION

This pilot study introduces a structured seven-stage framework for responsible human–AI collaboration and demonstrates its viability across three authentic undergraduate technology-course implementations. The framework moves students beyond passive AI use toward active evaluation, verification, and accountability — competencies that employers and academic institutions increasingly identify as essential. Two of three sessions produced higher post-assessment group means, and item accuracy was strong across most AI literacy categories, providing a promising evidence base for a more rigorous research program.

The findings reinforce what the literature on AI pedagogy predicts: responsible AI literacy is not acquired through exposure alone. It requires explicit, sequenced instruction that builds prompting skill, critical evaluation, verification habits, ethical awareness, and reflective practice within an integrated learning experience. The seven-stage framework operationalizes this sequence in a format that is practical, replicable, and adaptable across disciplines—making it a concrete tool for faculty who want to prepare students to work effectively and responsibly alongside AI.

The convergence of positive patterns across two sessions with substantially different baseline conditions — January, where students entered with limited and highly variable AI literacy, and June, where students entered already performing well — suggests that the framework has value across a range of student preparedness levels, not only as a remediation tool. This breadth of applicability, combined with the clearly defined research agenda established in the preceding section, positions this work as the foundation of a systematic, multi-phase investigation into structured AI literacy education in higher education.

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Evaluating the Need for a Mathematical Review Lesson in the Introductory Machine Learning Curriculum

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ABSTRACT
Postsecondary institutions are rapidly expanding Machine Learning (ML) curricula to meet skyrocketing industry demand. Many of them offer introductory ML modeling courses that focus on application and programming syntax. While students successfully learn the syntax to execute ML models, they frequently lack the foundational mathematical literacy in linear algebra, calculus, probability, and statistics required to interpret, debug, and optimize ML models. This review suggests that students need a structured mathematical review to ensure their comprehension of basic linear algebra, calculus, probability, and statistics to build a solid foundation to remove the pedagogical barrier that spikes student frustration and limits operational mastery.

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Keywords: machine learning education, mathematical literacy, curriculum design, linear algebra, calculus, probability and statistics, gradient descent

INTRODUCTION

When introduced to foundational ML mechanisms, including objective functions, optimization via gradient descent, and multi-dimensional feature scaling, students frequently experience significant cognitive load, encountering what can be termed a "mathematical impasse" *(*Nakamoto et al, 2025; Zheng & Gupta, 2020*).* This knowledge gap causes the study of ML modeling to be an opaque, "black box" experience. Students are incompetent in model evaluation, remain unable to diagnose problems, and fail to develop algorithmic intuition *(*Bueff et al., 2022; Guleria & Sood, 2022; Tedre et al., 2021*).* To address these pedagogical challenges, this paper investigates a critical curricular question: Does a prerequisite review of foundational mathematics enhance student comprehension of ML modeling?

WHAT DOES MODELING MEAN IN ML?

Machine learning (ML) involves training an algorithm on historical data so it can recognize patterns and produce a mathematical model capable of making predictions, classifying information, or automating decisions on new, unseen data. During training, the model iteratively adjusts its parameters until it converges—often across complex, nonlinear surfaces—to a solution that best fits the data. The following table lists the key phases in a typical ML modeling lifecycle.

Table 1 - Phases of the Machine Learning Modeling Lifecycle

PHASE	DESCRIPTION
Data Collection	The systematic gathering and measuring of data from different sources that will later be used for training.
Preparation	The iterative process of cleaning, transforming, and organizing raw data so algorithms can understand it.
Training	The model learns data relationships by exposing the algorithm to the prepared dataset, which iteratively adjusts its parameters to map inputs to desired outputs.
Evaluation	Evaluating the model against a separate, unseen dataset to measure accuracy, prevent bias, and ensure generalization rather than memorization.
Deployment	Deploying the verified model into a live system to process real-time inputs.

ML modeling techniques are generally categorized by the nature of the training data and the objective of the task. There are three basic techniques as shown in ***Table 2*** (see next page). Classification and regression are often used for supervised learning, while clustering techniques, such as K-means and Gaussian Mixture Models (GMMs), are used for unsupervised learning *(*Russell & Norvig, 2020*).*

Table 2 - Categories of Machine Learning Modeling Techniques

CATEGORY	DESCRIPTION	EXAMPLE
Classification	Predicting a specific category or label.	Determinizing whether an email is "spam" or "not spam".
Regression	Predicting a continuous numeric value.	Forecasting the price of a house.
Clustering	Grouping unlabeled data based on their similarities.	Segmenting customers into purchasing behavior groups.

These techniques are built on completely different mathematical logic and architectural structures. Each technique uses a completely different branch of mathematics to calculate its patterns. Without knowledge of basic math, ML operators cannot perform modeling analysis or troubleshooting (Bishop, 2006).

MATH USED IN ML MODELING

This paper categorizes the mathematics required for ML into three distinct levels: basic, intermediate, and advanced. The categorization is structured based on established university curriculum guidelines, standard industry pedagogical frameworks, and foundational textbooks (ASA/ACM, 2016; Bishop & Bishop, 2024; Deisenroth et al., 2020; Goodfellow et al., 2016; National Academies of Sciences, Engineering, and Medicine, 2018; Shalev-Shwartz & Ben-David, 2014; Wainwright, 2019).

Table 3 - Mathematics Levels and Their Usage in ML Practice

LEVEL	USAGE
Basic	Gasping algorithmic concepts and managing the basic data structures required for model inputs.
Intermediate	Tuning hyperparameters, debugging deep networks, evaluating metrics, and preventing overfitting.
Advanced	Designing new architectures, inventing optimization algorithms, or mathematically proving foundational model stability.

Table 4 divides ML mathematics topics to reflect how mathematics is applied to each level. The grouping is based on three core dimensions: the dimensionality of the data, the role of the practitioner, and the mathematical abstraction required.

Table 4 - Linear Algebra, Calculus, and Statistics Topics by Mathematics Level

LEVEL	TOPICS
Basic	• Linear Algebra (Foundations): Scalars, vectors, matrices, matrix multiplication, and transpose operations. • Calculus (Single Variable): Concept of a derivative, slope, optimization (finding local minima/maxima), and the Chain Rule for tracking composite functions. • Statistics and Probability: Mean, median, mode, variance, standard deviation, basic probability rules (independent vs. dependent events), and standard distributions (Normal/Gaussian distribution).
Intermediate	• Linear Algebra: Matrix factorization/decomposition, determinants, vector spaces, and principal component analysis (PCA) for dimensionality reduction. • Multivariate Calculus: Partial derivatives, gradients, Jacobians, Hessians, and vector-valued functions and analysis these functions. • Applied Probability and Inference: Bayes' Theorem, conditional probability, expectation, covariance matrices, Maximum Likelihood Estimation (MLE), Maximum A Posteriori (MAP), and hypothesis testing (p-values, A/B testing).
Advanced	• Advanced Optimization: Convex vs. non-convex optimization theory, Lagrange multipliers, KKT conditions, and stochastic approximation frameworks. • Statistical Learning Theory: Uniform convergence, Rademacher complexity, VC (Vapnik-Chervonenkis) dimension, and Probably Approximately Correct (PAC) learning. • Measure Theory & Functional Analysis: Hilbert spaces, Banach spaces, and measure-theoretic probability. • Differential Geometry & Topology: Topological Data Analysis (TDA) and Riemannian manifolds.

The dividing line for the Basic level is defined by single-variable operations and deterministic computations. The intermediate level is defined by moving from scalar mathematics into vector spaces, multi-variable spaces, and linear transformations. The advanced level is defined by moving away from concrete computation altogether and entering the realm of mathematical proofs, statistical bounds, and continuous infinite-dimensional spaces.

DILEMMA OF PEDAGOGY

Should students learn to build ML models from scratch, or learn to apply existing libraries (like Scikit-Learn or PyTorch) to assemble ML models?

Building an ML model from scratch means writing the mathematical formulas directly into raw code (like Python and NumPy) without using existing pre-made machine learning libraries. Linear regression, such as $y = mx + b$, is the simplest example. It requires students to: (1) start with a random slope (m) and intercept (b), (2) develop a repetition structure to compute the Mean Squared Error for all data points, (3) calculate the partial derivatives of the error with respect to m and b to determine the gradients, (4) subtract the gradients from the weights to find the gradient descent, and (5) iteratively repeat this process a number of times (such as 1,000 times) until the error stops shrinking.

Building a model leads students to design and develop algorithms, coding logics, and data processing. They can gain a deep understanding of modeling. However, building an ML model from scratch could consume too much instructional time and effort in the classroom, reducing active academic learning time. As a classroom exercise, students' models are often prone to bugs and are inefficient for large datasets.

On the other hand, using libraries to assemble models means leveraging highly optimized, pre-written code packages like Scikit-Learn (for traditional math models) or PyTorch as well as TensorFlow (for deep learning and neural networks). With the libraries these packages provide, students write a short Python script of high-level code similar to the following to build a model and see instant results.

```
from sklearn.linear_model import
LinearRegression

model = LinearRegression()

model.fit(X, y)

predictions = model.predict(X_new)
```

In the classroom, instructors can have a fast illustration and deployment using assembled or pre-built ML models. However, this pedagogy limits students' ability to debug failures, optimize performance, and adapt solutions to unique datasets. Students will miss the foundational knowledge required to make principled architectural changes.

NEEDS ANALYSIS

A needs analysis identifies the gap between what learners learn and what they should learn. The goal is to ensure the instructional materials and pedagogies are relevant and productive. This analysis argues: Can an ML practitioner build machine learning models without a good command of basic math?

The needs analysis starts with evaluating the feasibility of building ML models without math knowledge and progresses to a comparison of math prerequisites of ML careers (Tang & Saeedi, 2024). It also studies the roles played by Linear Algebra, Calculus, Probability, and Statistics in ML. A sample with three data points for a classic linear regression equation is used to visualize how simple math drives the mechanics of linear regression and gradient descent in ML modeling.

AUTOML AND MATH

There are many commercially available platforms, often called AutoML (Automated ML), designed to abstract the underlying calculus, linear algebra, and complex algorithms and to test many algorithms automatically, including decision trees, random forests, and logistic/linear regression. They provide GUIs (graphical user interfaces), drag-and-drop features, or simple natural-language inputs to allow users to assemble, test, and deploy ML models without a strong foundation of math. Some high-level libraries like Scikit-Learn, TensorFlow, and PyTorch also allow users to train, evaluate, and deploy ML models without a deep mathematical background.

Paleyes et al. (2022) examine AutoML platforms in production across various enterprise sectors. Schmitt (2023) confirms that enterprise-grade AutoML provides fast, reliable, and highly accessible frameworks for non-experts. Anna (2023) assures that AutoML platforms allow large teams to transition from experimental sandboxes to industrial, high-volume production environments while maintaining operational efficiency. Sampath (2025) outlines how AutoML platforms work in regulated industries. These studies and DataRobot (2026) point out that corporations have adopted AutoML tools to scale their ML pipelines. Below is a sample list of AutoML platforms.

Table 5 - Sample List of AutoML Platforms

PLATFORM	DESCRIPTION
DataRobot	• Provides automated preprocessing, feature engineering, and model selection for deployment with minimal math or coding expertise.
H2O Driverless AI	• Provides automated feature engineering, tuning, and interpretation via an intuitive GUI for users without heavy statistical backgrounds.
Google Cloud Vertex AI (AutoML)	• Enables cloud-based training and hyperparameter tuning for text, video, and tabular data.
Microsoft Azure Machine Learning Studio	• Provides a visual drag-and-drop workspace to connect datasets and modules for building predictive models without math.
AWS SageMaker Autopilot	• Automatically builds, trains, and tunes ML models from raw data without requiring manual algorithmic or mathematical adjustments.
KNIME Analytics Platform	• A low-code platform with a visual workflow editor where users connect nodes to read, transform, and model data.

The literature indicates that AutoML platforms do not eliminate the need for human mathematical expertise. While AutoML platforms automate the manual execution of building machine learning pipelines, the efficiency and effectiveness of the ML models are limited to the level of usages. Schmitt (2023) suggests that human ML operators are required to have a foundational grasp of statistics to audit the data beforehand and ensure quality of AutoML models. Hutter et al. (2024) state that human ML operators must possess a strong understanding of probability distributions, Bayesian theory, and loss function landscapes. Without an appropriate level of math competency, ML teams cannot properly define search spaces, leading to massive compute waste and poorly optimized models that fail in live production. Mehrabi et al. (2024) point out that ML teams must use probability and algebra to manually choose, configure, and correct mathematical trade-offs of the AutoML platform to avoid deploying a non-compliant model. Paleyes et al. (2024) discovered that when users did not understand the underlying linear algebra and matrix transformations of their data, they consistently fed invalid data structures into automated platforms. Guidotti (2025) asserts that an AutoML user cannot verify if a model is operating safely or logically without the calculus and linear regression knowledge required to properly read and critique these mathematical outputs.

ML CAREERS AND MATH PREREQUISITES

From the perspective of job performance, the latest literature emphasizes that, to ensure an ML model's accuracy in production, ML professionals must use appropriate levels of calculus to understand how the weights are updating, linear algebra to restructure the data vectors, and statistics to prove the system is reliable and safe.

Tang and Saeedi (2024) reveal that ML employers heavily filter candidates based on mathematical reasoning. Raschka (2023) explains why an ML engineer must mathematically prove their model actually works. Aris et al. (2025) depict how mathematical disciplines manifest as day-to-day machine learning workflows. Deisenroth et al. (2024) state that without a firm grasp of linear algebra and multivariate calculus, an ML engineer cannot debug optimization failures, handle high-dimensional embedding spaces, or customize loss functions. Zhao et al. (2023) confirm that ML practitioners must know matrix

multiplication (linear algebra) and probabilistic for modeling. Hullermeier and Waegeman (2024) prove why an ML engineer must understand probability to perform the job. Sun and Li (2023) outline why ML professionals must understand mathematical optimization to prevent networks from getting stuck during the training phase.

Table 6 uses three ML jobs to depict how the three levels of knowledge are required for ML careers. The job description of ML operators focuses on applying existing models to standard business tasks without altering the underlying machinery. ML engineers possess a deep understanding of software engineering and multi-dimensional matrix mechanics, enabling them to scale, optimize, and deploy models into production. They operate ML systems at the mechanical level, which is the level where ML operators manipulate the internal mechanics that make the model function. ML Algorithm Researchers focus on pure innovation, pushing the boundaries of artificial intelligence by developing entirely new mathematical frameworks.

Table 6 - Required Mathematics Level for ML Career Roles

JOB	REQUIRED MATH LEVEL	DESCRIPTION
ML Operator	Basic	Except for data entry, routine operation of ML models and maintenance of ML systems in production require a working knowledge of linear algebra, calculus, and statistics.
ML Engineer	Intermediate	A firm grasp of mathematics empowers ML engineers to diagnose architectural failures, optimize performance, and mathematically defend the integrity of their models.
ML Algorithm Researcher	Advanced	Without an advanced mathematical foundation, a researcher cannot formulate the theoretical proofs necessary to push the boundaries of artificial intelligence or safely scale models into uncharted computational territory.

Academic references, peer-reviewed curriculum surveys, and published textbooks explicitly outline the exact mathematical disciplines required for ML modeling into three core fields: Linear Algebra, Calculus, and Probability and Statistics (Deisenroth et al., 2020; Guidotti, 2025; Humpherys & Jarvis, 2020; Hutter et al., 2024; Kumar, 2024; Lan, 2020; Rasb, 2024; Research.com Editorial, 2026).

MATHEMATICS IN ML

Basic mathematics forms the theoretical foundation of ML, serving as the language used to translate data into algorithms. It enables practitioners to choose appropriate models, fine-tune parameters, and diagnose performance issues rather than treating algorithms as uninterpretable black boxes. While anyone can copy and paste machine learning code, understanding the math is what distinguishes good results from flawed ones. Below is a breakdown of the foundational math concepts required and exactly how they are applied to design, develop, and build ML models.

Table 7 - Roles and Applications of Core Mathematics Fields in ML

FIELD	ROLE	MAIN USAGE
Linear Algebra	Language of data	Understanding how tabular data is represented as a matrix.
Calculus	Engine of optimization	Indicating the direction of steepest descent, guiding iterative steps toward the global minimum error.
Probability and Statistics	Framework for uncertainty	Computing the likelihood of optimal convergence under conditions of high uncertainty.

LINEAR ALGEBRA

Linear algebra is how machine learning models store, manipulate, and process massive datasets efficiently. In ML, data is rarely treated as single numbers; rather, they are handled in chunks. Linear Algebra is essential for representing data and performing transformations. Machine learning models process features and images as arrays of numbers known as vectors, matrices, and tensors. It is the math behind operations like dimensionality reduction (e.g., PCA) and neural network computations. Below is a list of key knowledge of Linear Algebra used in ML modeling.

Table 8 - Key Linear Algebra Concepts Used in ML Modeling

FIELD	DESCRIPTION
Vectors and Matrices	Representing data: a single row (e.g., house features) is a vector, while an entire spreadsheet is a matrix.
Matrix Multiplication	The fundamental neural network operation; a model performs matrix multiplication when applying weights to features for predictions.
Transposition and Inversion	Essential for reshaping data matrices to enable correct multiplication.
Eigenvalues and Eigenvectors	Used in dimensionality reduction (like Principal Component Analysis [PCA]) to compress data while retaining the most critical information.

Gradient Descent is an optimization algorithm used to minimize an ML model's error by iteratively adjusting its internal parameters. Using Gradient Descent to optimize a simple linear regression is a common practice in ML modeling. The following is a classic linear regression equation which can be used to predict a target (*y*) from a single input feature (*x*).

$$\hat{y} = w \cdot x + b$$

where,

- *w* (weight) is the slope that controls how steep the line is.
- *b* (bias) is the intercept that controls where the line hits the vertical axis.

The following is a list of three data points to be used for training the ML model with a guessing initial value of *w* being 0.5 and b being 0.5 as well as the learning rate (α) being set to 0.1.

- (x=1, y=2)
- (x=2, y=4)
- (x=3, y=5)

The data point, (x=1, y=2), implies that an input of 1 is expected to yield an actual output of 2. The data point, (x=2, y=4), implies that an input of 2 is expected to yield an actual output of 4. The data point, (x=3, y=5), implies that an input of 3 is expected to yield an actual output of 5.

In ML, these initial numbers (w = 0.5, b = 0.5, and α = 0.1) are chosen deliberately to balance two things: giving the algorithm a starting point and controlling how fast it moves.

In simple linear regression, the loss function is convex, which is shaped like a perfect bowl. No matter where a ball is dropped into a bowl, whether at 0.5, 0, or -100, gravity (which is gradient descent) will eventually pull it down to the exact same lowest point. Starting both *w* and *b* at 0.5 is just a clean, arbitrary, non-zero neutral baseline.

The learning rate is the hyperparameter in optimization. It acts as a multiplier for our steps. 0.1 is a "Goldilocks number" for a small tutorial dataset. A hyperparameter is an external configuration setting that controls the ML training process. For example, the number of times the model will cycle through the entire training dataset is a hyperparameter known as "number of epochs." In science, engineering, economics, and machine learning, a "Goldilocks number" refers to a value that sits in a perfect, optimal middle ground between two extreme, undesirable states. In the real world, ML operators typically use a process called hyperparameter tuning to test different starting learning rates (like 0.1, 0.01, or 0.001) to see which one brings the model down the error hill the fastest without crashing.

Table 9 is a sample spreadsheet (SP1) that calculates the prediction ($\hat{y}$) and the error for each individual data point using the starting weights (w=0.5,b=0.5).

Table 9 - Sample Spreadsheet (SP1): Predictions and Errors for Initial Model Weights

Input	Actual	Predicted	Error	Squared Error
x	y	$\hat{y}$= 0.5x+0.5	($\hat{y}$−y)	($\hat{y}$−y)^2
1	2	**1.0**	**−1.0**	**1.0**
2	4	**1.5**	**−2.5**	**6.25**
3	5	**2.0**	**−3.0**	**9.0**

When feeding 1 as an input into the blindly guessed model with w=0.5 and b=0.5, the model incorrectly predicts an output of 1 instead of 2. When feeding 2 as an input into the blindly guessed model with w=0.5 and b=0.5, the model incorrectly predicts an output of 1.5 instead of 4. When feeding 3 as an input into the blindly guessed model with w=0.5 and b=0.5, the model incorrectly predicts an output of 2.0 instead of 5.

The fact that the model predicted a 1 when the expected (actual) answer is 2 means the model has a literal error of -1.0. Gradient descent uses this exact error to fix *w* and *b* so that the next time it sees an input of 1, its output will get closer to 2. Likewise, the model has a literal error of -2.5 when the input is 2 and a literal error of -3.0 when the input is 3. The result confirms to gradient descent that it needs to tilt the line upward significantly to correct the prediction mistake.

To calculate the gradients of *b* and *w*, use the following two equations. Gradient for the bias (b) is the literal error, which means that the mathematical direction and distance needed to move the bias is completely identical to how far off the prediction is from the actual target. The weight (w) acts as a multiplier or a volume knob for the input feature. The exact same adjustment to a weight will have a massive impact if the input is large, and almost no impact if the input is small. The weight gradient uses the input as a scaling sensor. The error tells the model how wrong it is, while the input (x) tells the model how

much leverage and what directional impact that specific weight has over fixing the mistake.

- **Gradient for** $b = (\hat{y} - y)$
- **Gradient for** $w = (\hat{y} - y) \cdot x$

Table 10 is a sample spreadsheet (SP2) that calculates the gradients for *b* and *w*.

Table 10 - Sample Spreadsheet (SP1): Predictions and Errors for Initial Model Weights

Input	b-Gradient (Error)	w-Gradient (Error × x)
x	$(\hat{y}-y)$	$(\hat{y} - y) \cdot x$
1	-1.0	$\mathbf{-1.0}$
2	-2.5	$\mathbf{-5.0}$
3	-3.0	$\mathbf{-9.0}$

In the classroom, the simple linear regression, $\hat{y} = w \cdot x + b$ is an ideal topic that depicts how linear algebra applies to ML modeling because it involves core concepts like cost functions, optimization, and evaluation metrics. Understanding these principles makes complex algorithms like deep learning more intuitive and manageable.

PROBABILITY AND STATISTICS

ML does not deal with absolute certainties; rather, it deals with likelihoods, patterns, and predictions. Probability and Statistics provide the framework for modeling uncertainty, analyzing raw data distributions, and making predictions on unseen data. Concepts such as conditional probability and Bayes' Theorem are core to assessing model accuracy. Statistics also validate whether a model's findings are real or just random noise. Below is a list of fields of Probability and Statistics used in ML modeling.

Table 11 - Key Probability and Statistics Concepts Used in ML Modeling

FIELDS	DESCRIPTION
Descriptive Statistics	Mean, median, mode, variance, and standard deviation: vital metrics for preprocessing, scaling features, and understanding data distributions.
Probability Distributions	Understanding data distributions (e.g., Gaussian, Binomial), which is critical because many algorithms assume specific distribution shapes.
Bayes' Theorem	Calculating conditional probability (an event's likelihood given another occurred), which forms the direct basis for Naive Bayes classifiers.
Hypothesis Testing & A/B Testing	Using p-values and confidence intervals to determine if a model's performance improvement is statistically significant or a fluke.

Loss Functions is a core application of statistical decision theory and predictive modeling. It is an example that can explain how knowledge of Statistics can lead to the design of a meaningful ML model. At its core, a simple linear regression attempts to find the best-fitting line that explains the relationship between an independent variable (*x*) and a dependent variable (*y*). The formula for the line is

$y = \beta_0 + \beta_1 x$.

To evaluate how well the line fits, ML models use a loss (or cost) function to measure errors. Simple linear regression uses Mean Squared Error (MSE), defined as:

$$\text{MSE} = \frac{1}{n}\sum_{i=1}^{n}(\hat{y}_i - y_i)^2$$

According to the SP1 spreadsheet ***(Table 9)***, the squared errors of the three data points are 1.0, 6.25, and 9.0. The current Mean Squared Error (MSE), which is the average of the squared errors column, is ((1.0+6.25+9.0)/3) = 5.42. The goal of the ML model is to make the MSE value as close to zero as possible.

Instead of manually calculating every scalar multiplication across multiple tables, this paper summarizes the single-step weight update in a single overview as shown in table SP3 ***(Table 12)***.

Table 12 - Sample Spreadsheet (SP1): Predictions and Errors for Initial Model Weights

Data Point (x, y)	Initial Prediction $(\hat{y})$	Initial Error	Updated Prediction $(\hat{y}_{new})$	New Error	Squared Error $(\hat{y}-y)^2$
(1, 2)	1.0	-1.0	1.717	-0.283	0.080
(2, 4)	1.5	-2.5	2.717	-1.283	1.646
(3, 5)	2.0	-3.0	3.717	-1.283	1.646
				Average	1.124

With the adjustments, the new MSE yields 1.124, which is the average squared error for the three new predictions. This reduction in Mean Squared Error (from 5.42 down to 1.124) illustrates why statistical loss functions are critical for model evaluation. Without understanding matrix structures and error scaling, students treating libraries as "black boxes" cannot diagnose why high-dimensional feature vectors fail to converge or why invalid matrix shapes lead to silent pipeline errors in production.

CALCULUS

If linear algebra represents the structure of the data, calculus is what allows the model to actually learn from it. Calculus is the tool used to minimize errors and maximize accuracy. It is crucial for optimization. Training a model means iteratively minimizing its errors. Calculus uses gradients and derivatives (via algorithms like gradient descent) to update model parameters and find the optimal weights. ***Table 13*** is a list of fields of Calculus used in ML modeling.

Table 13 - Key Calculus Concepts Used in ML Modeling

FIELDS	DESCRIPTION
Derivatives	Measures the rate of change to show how tweaking a specific weight alters model error.
Partial Derivatives & Gradients	In models with millions of variables, partial derivatives calculate the error rate for one variable while holding others constant; the gradient is the vector of these derivatives.
Gradient Descent	The primary ML optimization algorithm; it uses gradients to take sequential steps "downhill" to find the minimum error rate.
The Chain Rule	The backbone of backpropagation; it allows neural networks to pass error signals backward through multiple layers to update early weights accurately.

The simple Linear Regression $\hat{y} = w \cdot x + b$ can be used to demonstrate how calculus drives ML modeling. The sample ML model used in this paper is to predict a value (y) based on an input (x). The goal of linear regression is to find the equation of a straight line that fits these three points, (1, 2), (2, 4), and (3, 5), as perfectly as possible.

For simplicity, let the bias *b*=0, so the error equation is simplified to:

$$\hat{y} = wx$$

The above mathematical illustrations lead to the development of a loss function equation based on the MSE. First, let the average error be represented by the letter *E*, which can be expressed as:

$$E = \frac{1}{n}\sum_{i=1}^{n}(\hat{y}_i - y_i)^2$$

Second, with a given guess of weight (*w*), apply the three data point to the error equation, $\hat{y} = wx$, to obtain:

- For (1, 2), $\hat{y}_1 = (w(1) - 2) = (w - 2)$
- For (2, 4), $\hat{y}_2 = (w(2) - 4) = (2w - 4)$
- For (3, 5), $\hat{y}_3 = (w(3) - 5) = (3w - 5)$

The total loss function, *E(w)*, becomes

$$E(w) = \frac{1}{3}[(w-2)^2 + (2w-4)^2 + (3w-5)^2]$$

Calculus helps to find the optimal weight (*w*) that minimizes the prediction error of the ML model. This loss function forms a parabola (a U-shaped curve). The lowest point on this curve represents the lowest possible error, where the slope of the curve is exactly flat (zero).

Rather than focusing on manual derivative computation, the instructional focus shifts to interpreting the derivative as an optimization signal. Evaluating the derivative at *w* = 1 yields a negative gradient (dE/dw ≈-7.33), which mathematically indicates that increasing the weight will decrease total error. Below is the equation that updates the weight.

$$w_{new} = w - (\alpha \times \frac{dE}{dw})$$

With w = 1, w_{new} is 1.366, as shown below.

$$w_{new} = 1-(0.05 \times -7.33) = 1.366$$

Try using the new w = 1.366 to obtain the errors of the three data points:

- For (1, 2): $((1)\times1.366 - 2)^2 = 0.$
- For (2, 4): $((2)\times1.366 - 4)^2 = 1.$
- For (3, 5): $((3)\times1.366 - 5)^2 = 0.$

The new error E_{new} is 0.94. In a single step driven entirely by a calculus derivative, our total model error plummeted from 3.0 down to 0.94.

$$E_{new} = \frac{0.402+1.608+0.814}{3} \approx 0.94$$

This simple three-point example perfectly illustrates why a foundational understanding of calculus is essential for mastering ML. Calculus is the mathematical engine of ML. Teaching ML without calculus is like teaching someone how to tune a high-performance racecar engine without explaining how internal combustion works.

MATH READINESS OF STUDENTS

Literature is rich in explaining why a significant portion of incoming U.S. college students lack the required linear algebra, calculus, and probability skills. For example, a formal petition signed by over 1,000 University of California faculty members explicitly stated that incoming undergraduates are demonstrating "severe preparation deficits" in math (Belkin, 2026). UC San Diego revealed a massive surge in students failing to meet basic college-level math benchmarks (University of California, San Diego Admissions Workgroup, 2025). The federal government's longitudinal tracking of 12th-grade math scores showed that high school seniors reached their lowest levels on record, with 45% of graduating students scoring "below basic" in core mathematics proficiency (NCES, 2025). Annual standardized testing metrics reveal that only 27% of female students and 32% of male students nationwide achieved the minimum college-readiness benchmarks in mathematics (ACT, 2024). National Academies of Sciences, Engineering, and Medicine (2024) reports that nearly 40% of incoming students at traditional four-year universities and 70% at two-year institutions require non-credit developmental math courses. Moran-Soto et al. (2025) point out that without structured "bridge" or remedial math interventions to correct specific algorithmic logic,

students experience extreme math anxiety and opt out of technical majors.

FUTURE EMPIRICAL RESEARCH

While this manuscript provides a conceptual analysis and literature synthesis on mathematical requirements in machine learning, empirical research is needed to validate specific instructional interventions in the classroom. Future studies should evaluate and compare student learning outcomes across different mathematical preparation structures. Specifically, empirical investigations could focus on:

- Comparative Model Evaluation: Conducting quasi-experimental or randomized trials to compare the effectiveness of a standalone, pre-semester "math bootcamp" against embedded "just-in-time" mathematical review modules integrated throughout introductory ML courses.
- Student Performance and Retention: Tracking quantitative metrics—such as model debugging proficiency, hyperparameter tuning accuracy, and overall course completion rates—among students entering with varying levels of prior mathematical preparation.
- Affective Measures and Math Anxiety: Assessing changes in student confidence, self-efficacy, and perceived cognitive load when attempting to interpret and optimize machine learning algorithms following structured mathematical reviews.

CONCLUSION

College students need a focused review of fundamental mathematics before beginning machine learning (ML) coursework, because math is the language that makes ML concepts transparent rather than mysterious. Without this foundation, algorithms quickly become black boxes, making it difficult for students to debug models, tune hyperparameters, or interpret code behavior. A structured preparation model helps eliminate these barriers and builds mathematical fluency essential for success.

A practical approach is a one-week math bootcamp offered before ML instruction begins. This short intensive course reinforces core concepts in linear algebra, calculus, probability, and statistics through targeted lessons and hands-on practice, giving students the tools they will immediately apply in modeling. Complementing this, just-in-time review modules embedded throughout the ML curriculum provide brief refreshers exactly when students need them—such as revisiting gradients before teaching gradient descent or reviewing matrix operations prior to PCA—helping students connect math concepts directly to algorithmic applications.

To support these strategies, programs should establish clear prerequisite math competencies, including comfort with vectors and matrices, derivatives and optimization, probability rules, and basic statistical reasoning. Students who need additional preparation can follow hybrid models that blend self-paced online review with instructor-guided workshops or supplemental labs. Together, these approaches create an efficient mathematical onboarding system that reduces frustration and equips students for meaningful engagement with machine learning.

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FROM THE CLASSROOM:

The Future in Online Teaching and Student Learning From An AI Perspective

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ABSTRACT

This article examines the evolving roles of teachers and students in higher education as artificial intelligence and digital technologies increasingly reshape online learning environments. Over the next one, five, and ten years, educators are expected to transition from traditional content delivery toward roles centered on facilitation, mentorship, ethical oversight, and the design of personalized learning ecosystems. At the same time, students will become more autonomous, data-informed, and actively engaged as co-creators of knowledge, leveraging AI-driven tools to customize learning pathways, collaborate across digital networks, and demonstrate mastery through authentic performance-based experiences. The article explores how adaptive learning systems, intelligent feedback mechanisms, and hybrid instructional models will transform teaching practices, learner engagement, assessment strategies, and the balance between human expertise and artificial intelligence in education. Accompanying charts illustrate projected trends in instructional innovation, technology adoption, learner behaviors, and the evolving partnership between educators and AI-supported learning systems. Together, these developments suggest a future in which the enduring value of educators lies in cultivating critical thinking, ethical reasoning, creativity, collaboration, and intellectual resilience within increasingly technology-enhanced learning environments.

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Keywords: AI in higher education, online learning environments, AI and technology reshaping education

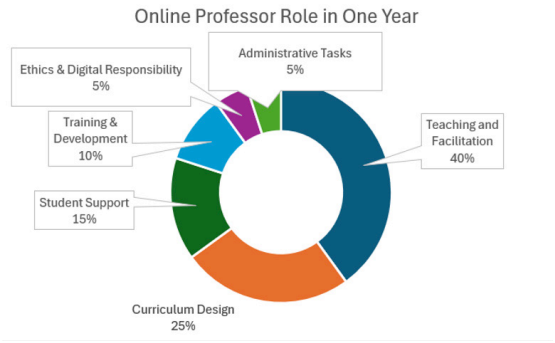
INTRODUCTION

There has been growing concern about what the online classroom will look like for teachers and students with the inclusion of Artificial Intelligence (AI) in the teaching environment. This article that looks at what happens from the AI perspective and how the changing role of the online teacher keeps their employment intact and more necessary than ever. It also addresses the changing role of online students and how their learning adjusts over time.

ONE YEAR FROM NOW: ONLINE PROFESSOR HIGHLIGHTS

A year from now, the online college teacher's role will still be recognizable as it is today, but it will be meaningfully reshaped using AI (see ***Table 1*** and ***Figure 1***). The shifting of student expectations and institutional pressures will be important to keep on the forefront of our thoughts. The biggest change isn't in replacing the teacher; it's in redistributing their effort.

Figure 1 - Online College Professor Role in One Year



Source: *OpenAI, (2023).*

Table 1 - Online College Professor Role

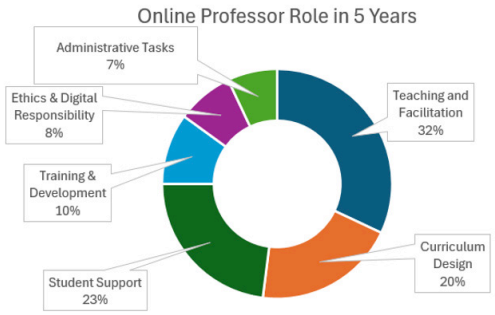
ONLINE COLLEGE PROFESSOR ROLE	DESCRIPTION
Teacher Role	Shifts from content experts to learning coaches and mentors.
Student Care	Identifies struggling students in a personalized manner while also taking on stronger mentoring and career-coaching roles.
Ethics	Moves to the center of teaching: academic integrity, bias, privacy, and workplace applications of AI.
Curriculum Design	Becomes faster and more career-focused, where AI helps faculty create and update lessons, activities, and assessments more frequently.
Teacher Strategies	Shifts toward active, hands-on learning, with less lecturing and more facilitation, discussion, and real-world applications.
Administrative Tasks	Becomes partially automated (grading, feedback, content creation), with faculty facing increased demands for student outreach, compliance, and student use of AI is appropriate.
Faculty Training	Occurs more often.

Source: *OpenAI, (2023).*

FIVE YEARS FROM NOW: ONLINE PROFESSOR HIGHLIGHTS

Online Learning in five years: an online college class will feel less like a set of videos and discussion posts and more like a guided, interactive learning environment that blends AI support, real-time interaction, and career-focused work (see ***Table 2*** and ***Figure 2***).

Figure 2 - Online Professor Role in Five Years



Source: *OpenAI, (2023).*

Table 2 - Online College Class in Five Years

ONLINE COLLEGE CLASS IN FIVE YEARS	DESCRIPTION
Flexible, Structured Format	Students won't just "log in and watch;" they'll actively participate.
AI Supported Learning	AI becomes a built-in tutor, not a replacement for the professor.
Short, Interactive Content	Learning is broken into engaging, manageable pieces.
Active Learning & Projects	Students apply knowledge, not just memorize it.
Collaboration and Community	Less isolation, more community-building.
Personalized Learning Paths	Learning becomes more individualized; feedback is continuous.
Skill & Career Integration	Focus shifts to career readiness, not just course completion.
Emphasis on Digital Ethics	Ethics becomes a regular part of coursework.

Source: *OpenAI, (2023).*

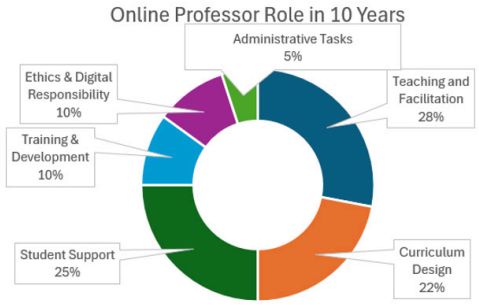
COMPARISONS FROM ONE TO FIVE YEARS

One category that will change is Student Support, with an 8% increase from one to five years. Students will see greater use of the online professor's time with a shift to include more mentoring, career coaching, and continuous feedback. Another highlight will be Teaching and Facilitation, with a decrease of 8%. Teachers will less likely be leading a lecture and more likely be mentoring and providing personalized lessons for the students. Curriculum Design will see a difference of 5% less contribution from the faculty and more from the AI Agent.

10 YEARS FROM NOW: ONLINE PROFESSOR HIGHLIGHTS

Online Learning in ten years: an online college class will likely feel less like a "course website" and more like a continuous, immersive learning ecosystem. The structure of semesters and static modules may still exist, but the experience will be highly personalized, interactive, and deeply connected to real-world work (see ***Table 3*** and ***Figure 3***).

Figure 3 - Online Professor Role in 10 Years



Source: *OpenAI, (2023).*

Table 3 - Online College Class in 10 Years

ONLINE COLLEGE CLASS	DESCRIPTION
Fully Personalized Learning Paths	Students follow a custom pathway. The class becomes adaptive, not one-size-fits all.
AI as a Built-In Learning Partner	AI handles routine support and instructors focus on higher-level thinking.
Immersive & Interactive Environments	Virtual Simulations & Labs; learning becomes experiential, not just theoretical.
Project-Based, Real-World Learning	The course feels closer to doing a job than taking a class.
Continuous Assessment (No traditional exams)	Less emphasis on tests, more on demonstrated ability.
Strong Collaboration Networks	Online learning becomes social and connected, not isolated. Students work in Global Teams.
Instructor as Mentor & Strategist	Less lecturing, more coaching and guidance.
Integrated Ethics & Digital Responsibility	Ethics becomes embedded, not a separate topic.
Lifelong Learning Model	Micro credentials: learning becomes continuous, not limited to a semester.

Source: *OpenAI, (2023).*

COMPARISONS FROM ONE TO FIVE TO TEN YEARS

Ethics & Digital Responsibility will increase by 2% from the five to ten-year view and doubled from the first-year view to a 10% contribution by faculty. Facilitating the classroom will decrease from five to ten years by 4%, giving rise to AI's contribution over faculty alone. Compared to a one-year view, Teaching and Facilitation will drop from 40% to 28% of the faculty's time. Student Support will shift from 15% to 25% from year one to year ten. Faculty will increase their overall time in direct student communications.

COMPARISON OF THE STUDENT ROLES IN ONE AND FIVE YEARS

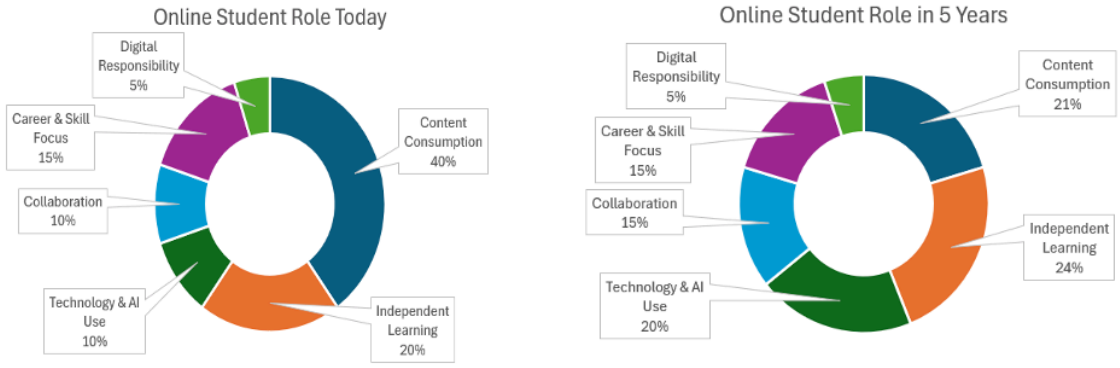
Students will become more proactive with their learning responsibilities by focusing their time collaborating with others (up 5%) and on independent learning (up 4%). Technology use will double from 10 to 20%, demonstrating higher attention to AI. On the flip side, Content Consumption (assessing digital and traditional media) is where students will see a more complete and valuable use of their time (see ***Table 4*** and ***Figure 4***).

Table 4 - The Changing Student Views of the Online College Student

THE ONLINE COLLEGE STUDENT TODAY	ONE YEAR	5 YEARS
Uses AI occasionally	Uses AI routinely	Uses AI and digital tools daily for learning
Adapts to flexible learning	Expects flexibility by default	Participates in interactive and project-based learning; doesn't rely heavily on lectures
Is career-focused	Hyper-focuses on Return On Investment and employability	Focuses on skills, experience, and career readiness
Balances digital and traditional learning	Relies heavily on integrated digital learning systems such as Apps and Networks (digital ecosystems).	Finds balance between digital learning and traditional learning practices, rather than a completely virtual or completely traditional model. Technology becomes more integrated into education, but students still need human interaction, structured guidance, and foundational academic skills.
Seeks support services	Expects proactive personalized support	Offers more personalized, proactive, technology-supported learning that is available almost continuously. Colleges focus not only on academics, but also on student well-being, career readiness, and engagement because online learners often need stronger connection and support systems.
Learns from instructors + internet	Learns from instructors + AI copilots	Experiences more flexible and personalized learning; no more fixed course structures

Source: *OpenAI, (2023).*

Figure 4 - Comparison of the Student Roles Today and in Five Years



Source: *OpenAI, (2023).*

CONCLUSION

AI is changing both the student and faculty roles with various forms of communication and connection. Faculty will take on more responsibility working with the individual students and developing a personalized learning plan. We may see a stronger need for a background in psychology as the student spends more time networking with the faculty than ever before. The faculty need to ethically guide the students' use of technology as they traverse through their educational path. Overall, AI will change the way students learn and faculty teach.

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This paper would not be possible if not for the idea from William (Bill) Garrison, who had the original idea of what a teacher would look like in five years using an AI perspective. Thank you, Bill!

AI ACKNOWLEDGMENT

AI process used: AI was used throughout the document to edit and outline as well as to generate tables. (Prompt: What will a college teacher's role look like in one, five, ten year(s) as per student care, ethics, curriculum design, teaching strategies, administrative tasks, and training?)

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CASE STUDY:

Beyond the Competition Paradigm: AI, Business and the Relational Future

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1. INTRODUCTION: AI AND THE COMPETITION PARADIGM

Today we are who we are as humans, and yet we are becoming even more. This case study argues that AI should not be implemented primarily through a fear-based competition paradigm but through a relational business paradigm that balances efficiency with human development, social stability, and shared responsibility, resulting in organizational effectiveness.

For centuries, we have grown in our approaches to business based upon our environment and culture. We moved centuries ago from a matriarchal, nurturing and giving society to a masculine, achievement-focused, competitive society. The history of the industrial age was described by Zinn (1995) and Greenberg (2017). In the West, we have espoused that competition is good. We believe as we get more things, we have a better life. The feelings and emotional high of winning outweigh caring for others beyond ourselves and our small tribes. Unfortunately, this premise has harmed our society by depleting resources that could be used more efficiently and effectively elsewhere. Heffernan (2014) showed the disadvantages of competition.

We see the results today in the US and with those countries that emulate our culture with a similar focus and implementation. We focus on getting what we want even if it costs others. Language is used in metaphors and analogies to support this perspective. In fact, we are propelled with this AI driven mantra of "those who will survive are only those who know and use AI." This mantra is a fear-based premise, and it has become a mantra through repetition of common language.

2. THE FEAR-BASED MANTRA CREATES THE CASE OF AI

From a business perspective, we have had so much historical economic growth as humans moving from individual crafters to civilized society, then to the formation of small businesses growing into large businesses and corporations. The amazing result of this competition led to an interdependence of companies, employees and customers, and even societies with each other. It was based upon competing to win the prize to make more money with power and control.

Competition is based upon the value of winners and losers. Initially, it feels great to win but detrimental to lose so we are compelled to win without caring about others.

The AI tech company leaders saw how power could be gained in the game if fear was used to control the game. Neurolinguistic programming phrases, metaphors and analogies were used to build the fear in people creating a new direction for humanity. This case study shows how the introduction of AI has changed the direction of humanity including economics, intellectual development, and human capacity.

The AI companies' use of fear messaging of losing the race has extended to countries pitted

against each other in broader competition of who can create the better and best Agentic AI to use in military defense and offense.

AWAY FROM FEAR TO POSSIBILITIES

What if we are missing out on a better life given we are stuck in the competitive fear-based business paradigm? What if we could all win? This has happened in the past. Can it happen again? Yes, it can.

What if we could move into a community of AI possible business paradigm of becoming more with the assistance of AI not the takeover by it. It's a matter of choice, our choice.

What if we had another mantra to help us achieve a new level of human AI future.

"We know AI will assist us to become better at what we do because we use it to assist our thinking capacity without allowing AI to erode our own capacities. We see AI as an associate."

There is still time to choose to avoid fear and to embrace learning and growing emotionally and spiritually as well as intellectually.

Artificial Intelligence bots and agents could propel all of us including our leaders toward this mantra formulating a new business paradigm that can be transitioned through the planning and choice of many options supported by those in charge of the AI technology, government by the people, large and small business, and those who are using and affected by AI.

Today with the introduction of AI, there is an opportunity to create a new business paradigm based upon integrity, kindness, generosity, authenticity and gratitude. Now and in the future, humans will need to stay focus on their thinking skills and behaviors while using AI to support but not absorb an independent life of self-direction and hard work. We need to embrace the realization expressed by authors like Angus Fletcher (2025) in Primal Intelligence who states that while genius can be strengthened within the human species, this is not the case with computers. The potential for humanity is to collaborate with AI and each other. To develop that human genius, a supportive paradigm for business and society needs to be created. With the application of this new paradigm, humans can do more with what AI can do for us without losing ourselves or our capacities to think clearly, independently and critically. The solution starts with a new realization: we are so much more than AI and its speed to emulate our capabilities.

3. NEW BUSINESS PARADIGM YIELDS EFFICIENCY WITH EFFECTIVENESS

Recently I saw this new relational Business Paradigm exhibited in Japan. As I traveled through the train stations of Tokyo, I saw people running to catch the trains and being stuffed like sardines in containers moving quickly to the next station. People exiting quickly and yet the doors stay open as long as people move out. I see people helping people to move quickly when entering or exiting the trains. The trains don't move until all the passengers are on or off. They are programmed to create safety and yet the people are programmed for efficiency and move quickly. The underlying values are courtesy and efficiency. It's a forum of where efficiency meets effectiveness. Both are needed to have a balanced business environment.

When one gets out of balance such as letting AI do it all, the effectiveness and ultimately the profits will go down. We live in an interdependent world. We need to plan for a transition of AI as a new species in our lives but not the only one. For example, AI creators are generating more and more AI agents to take over routine tasks without considering the graduating students who need these entry jobs and tasks to develop their experience in the corporate world. Leaders need followers who can support their leadership. Respect for humans at all ages and incomes are a part of the interdependent economy. Corporate leaders need to look out into the future and realize in this interdependent economy, businesses need customers who have jobs so they can continue to buy the business' products and services. What happens if AI does all the jobs?

4. THE HUMAN AND ECONOMIC RISKS

Let's look at the current AI mindset and its projected timeline with the consequences.

The AI mindset supports the philosophical perspective of the method versus reflecting about the result of focusing on the next efficiency. Here is a simple formula to consider in this case study of AI and its long-term effects.

AI Efficiency leads to:

- Reduction of labor costs for organizations, this results in
- More profits then = stock prices increase until the massive job layoffs create
- Loss of customer purchases = there is a significant number of fewer customers
- Lower sales volumes = lower profits and stock prices

In this AI world, the excitement of building and achieving has outweighed the strategic planning and reflection of seeing the timeline impacts when AI replaces 95% of the jobs.

Both thought leaders and tech leaders are focused on AI efficiency and the need for massive data centers to support the machine of AI. Again, looking at the methods and how to create this future of AI everywhere.

THE CONSEQUENCES OF MORE AI USAGE

People in communities are reacting to the data centers' enormous need for their electricity, water and land. Competition will present new problems between people and the requirements of AI until a new energy and cooling technology is developed.

Executives in many companies are driven by short financial gains, are willing to eliminate white collar jobs without looking at long term losses of profits and the value of corporate history decision making. There are even possibilities of AI taking over executive jobs.

So what are the unintended consequences in this kind of world if it continues at its projected pace?

Many job losses will lead to people accessing their savings earlier than planned. The lower economic class will be living in poverty and without homes. Community mental health may resurface as major issue. Younger unemployed people may feel hopeless. More choices will be needed for all displaced people.

Some would say "well you can live on a basic income." We foresee a different reality of survival if this is the solution. Will people turn to just entering the matrix of dreams or games? Imaginary competition? Or spending their days in entertainment? Will they retreat to natural communities?

What's next beyond the paradigm of competition?

The current trajectory of AI expansion is one where not just jobs will be lost; corporate history and whole segments of our society's creative jobs are disappearing because businesses want to create efficiency. The first to be displaced and disconnected from their work were graphic designers, journalists, public relations, marketing, writers of movies and books. Who cares? We should have because next it was accountants, lawyers, doctors and teachers.

HOW DID THIS HAPPEN?

The original creators of AI saw solutions that could be created by accessing all the knowledge in the world. Then the possibility of personal gain was realized because of what AI could do that people wanted. Someone in the beginning of the financial sector saw there was a need for persuasion including how to overcome the objections of those who saw the future and were concerned. The goal was implementation without reflection and planning to see if society was ready and if not how to prepare it, so these chaotic transitions were managed.

Their plan was clear: just use highly persuasive language and metaphors to challenge those who disagreed with the possible downside of this efficiency promotion. The first linguistically persuasive method was comparing resistance to previous times with resistance to calculators.

Then resistance was dismissed with a comparison to the Industrial Revolution, where jobs changed but all was all right in the end according to these promoters of AI, who are not historians. The historians saw the general premise but not for everyone. Ware (1990) describes a different picture of the Industrial Revolution that was very disruptive for people, the climate, and home life.

Many people just accepted the false premise without researching the history. The fantasized perspective of the Industrial Revolution is now used as a factual reference to a very different revolution.

Underlying this false premise was an inference that people who resist are wrong and possibly not as bright as those proposing AI technology for cost savings.

This present AI transformation is different from the Industrial Revolution because it eliminates jobs that are not replaced by similarly skilled and white-collar positions. Leaders see cost reduction of labor costs affecting their bottom line for short-term gains. Wise executives have begun to question the value of AI efficiency programs and their long-term effects in an interdependent global society of workers as buyers.

WHAT NEXT?

What happens in the next few years, if the remaining jobs are just servicing AI programs for more efficiency resulting in high unemployment worldwide?

Where do people go? This is the challenge where the promoters say people will just adapt and find new jobs. Will these be comparable paying jobs? One option, data adapter jobs, pay far less than coding jobs and it is feeding the AI machine learning more than all humans combined.

So, is there only one solution that serves those in power and those with the most to gain? They want to promote competition for the newest and emergent technology based upon the fear of loss of opportunity.

5. THE FORK IN THE WOODS CASE STUDY

There are two or three other pathways in the woods. Maybe more.

No one predicted what we are experiencing and few see what is ahead in the new business world. It's as if we are walking in a wood filled with many trees and bushes. Some are identifiable and some are just glimmering in the sunshine. As we walk along this new path, we come to a fork in the woods. We can go left or to the right. Each path has a hill that obstructs our view of where it heads. There are signposts but they are written in an unusual language that we don't understand. So, what to do next? We can turn around and return to past lives or hide in the forest, hoping the AI falcons won't swoop down to grab and eat us.

We need to choose because the wild animals are behind us and they are pushing us through fear to move forward along the left path to avoid being eaten alive. We hear the screams of those who don't choose.

There are several camps with their own theme songs, flags and tents. Each is camped at the fork in the woods. Or on the left path, we see…

The hyper promoter AI camp sees how great each new technology will be for business and executives who want more efficiency. While most of this is true, there is so much potential and some are beginning to realize the potential risks such as cybersecurity, or AI out of the creators' control becoming self-autonomous. Societal issues are created such as high unemployment, loss of tax revenues, homelessness numbers are increasing. The result? Greater society support will be needed but the treasuries are limited and diminishing without additional support coming in.

As we have discussed, the current business paradigm has existed for centuries based upon competition of winning and the fear of losing. We see it from marketing to sales. We see it from a consumption perspective of the more you have and show, the more people believe you are a winner. You have succeeded in the competitive market. When globalization occurred in the 1980s

and 1990s, the competitive business paradigm was reinforced through lower prices because of lower labor costs that pushed greater profits for companies. All was good.

Principles including more is better, coupled with the outsourcing of manufacturing to poorer countries has hurt so many people and inner cities across the U.S. Now these poorer countries are losing their people's call center jobs. Competition is counterproductive to the building of society (Kohn, 1987).

CONSUMPTION

In this competitive paradigm, the AI technology companies continue to develop and promote their updates as the next best thing. And yet, there are issues that are whispered in the hallways about legal issues, warfare, hallucinations (really mistakes but quickly described as hallucinations), CFOs are watching the funding going out the door and have begun to ask the CIOs to show the real return on investments. There have even been articles stating that CIOs are getting nervous because like the dot coms of the 90s, the speculation may not return what it promised. At the same time, CEOs are choosing to slow some of the process of exchanging humans for AI agents and robots. While it may be true, AI is more efficient in some tasks, more measurement and proof is needed beyond the statements of those who stand much to gain. This is in America.

What about other cultures like those in Europe, China and Japan? How does culture affect the acceptance of AI and where is it being implemented and why? These other countries have similar competitive perspectives and yet different ones too, where the needs of their humans take precedent over the needs of the developers.

Then there is another camp on the path where the wisdom of ancient civilizations resides. We can see where the AI transformational future might be okay and even wonderful if we can look at it from this perspective and choose a new direction for our future course.

This is not just a major technological change, but it is a major economic and societal change to be absorbed or created to serve all of us or only a few of us. As always, the choices are ours to react to, control or both.

Another path to the right leads us to the AI Leadership Summit.

As part of the Leadership Summit, leaders from business, government, associations, small business owners, employees, parents, educators, doctors, mental health professionals and teens will come together to look at the broader picture from the history described here to see what is possible and what is to be avoided.

6. REASONS WHY THE RELATIONAL BUSINESS PARADIGM WORKS

The new business paradigm could emerge from AI development and implementation. As jobs are eliminated and AI support jobs from data entry to AI service jobs occur, there is an opportunity for many to develop new options from the corporate world where people can grow and develop beyond their rush of living to the next future moment.

They might develop a new awareness of the present possibilities and life of just enjoying their thoughts and new crafts or businesses.

The question is how we get millions and ultimately billions of people moving into this new paradigm of the collaborative community working in teams away from the competitive challenge of the bear in the woods. In a recent article of *Wired*, it was noted that the predominant nations of China and the U.S. should put their competition aside and work together (Knight, 2026). Collaboration as a method and process was also mentioned in the book *AI Superpowers China, Silicon Valley and the New World Order* by Kai-Fu Lee (2018). He proposes that the problems created by AI are too big to solve by one country.

Nations need to collaborate, but no one seems to go to the next step of how and who specifically collaborates. It needs to move beyond the

national level to government and companies that sell these products to help displaced humans into new work or independent business.

The new business paradigm that will be developed in a timeline where people are able to build new businesses or take on new jobs. This needs to be planned to avoid crisis management and huge disruptions. People need to be able to adapt quickly and flexibly because there will be countless obstacles ahead including the loss of regular income and the consumption of their savings. When people face this situation, what percentage of the population will be able to survive? AI bots like Claude will help and encourage them via their thinking and planning capabilities. Claude is an amazing assistant to help us reflect and think about our situations and relationships. Yet, we need more to build our own "what if" planning skills.

THE CHOICE IS YOURS, OURS?

What if you could live in a society and culture that respected itself, you and others? It showed these values through action, not just words. The words used are spoken with respect, not just naming it but showing it.

Would you want to continue to live in a society and culture which promoted competition and being a winner at all costs? What does this create in you? Your loss of emotional and spiritual health? The fear-based mantra spoke of how you could win and if you didn't seek it, you would lose something very important to you. The right words sink into your stomach promoting fear of losing so you go for what is promoted because you wouldn't want to lose out.

This new relational and collaborative AI business paradigm could be the shining example of a caring and collaborative community, where people can be their authentic or true selves because they are respected. Even strangers are respected. What if even toddlers can play without adult attention because the parents know it is safe. You are whole in yourself, and you care about others; in fact when you see a need, you offer to fulfill it. It's a society of caring because it recognizes people using technology to serve their needs versus just getting more.

Within the new relational/collaborative paradigm, AI technology is developed for the people. It preplans for the use of technology to serve the people. Japan is that society with these values being implemented.

We are at that fork in the woods where we have many options to select from but there are two main paths, one leading to the left and one to the right.

The one to the left is built on serving the ego of self while using their own and others' fear. Competition results from the fear of loss, so it pits people against each other.

The one to the right seems like a new path. Yet there are living communities that exist with a community of respect with discovery of the people's needs and then providing those. It's a society of caring using the benefits of AI for the people, all people. AI is not just a technology; it is a gift for all people. On this path, culture influences everyone and everything, including the development of this wonderful technology. It brings it to people who need AI's help.

7. A TRANSITION PLAN FOR WORKERS, BUSINESSES, AND COMMUNITIES

We have an exigence-driven choice to make the transition to a better future. The AI Leadership Summit concept described in this case study requires planning with leaders from higher education, technology company leaders, corporate AI clients, small business owners, young people, older people, Chambers of Commerce, federal and local government visionaries to come together to develop the transitional path to the right path. The AI Leadership Summit could make this happen with specific strategic planning for the transitional timeline to the right path for all.

8. CONCLUSION: CHOOSING THE RIGHT PATH

From the AI Leadership Summits, we can see an organized, friendly, adaptable, planning process with the value of alignment of all people to build a new infrastructure for pursuing the path to the right in the forest. There's still time, but not much. We can do it because the other path leads to destruction.

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FACULTY TEACHING NOTES FOR LEAD570
This case study offers an alternative view of what AI Leadership challenges and opportunities might be. Therefore, it could be used in the Online Discussion or in a Live Lesson discussion within one of weeks 1, 2, 6, or 8 to enhance the conceptual thinking of the students as leaders.

WEEK(S) 1 AND/OR 2

COURSE OBJECTIVES (COS)

CO 1: Assess leadership strengths and opportunities in the age of artificial intelligence.

CO 2: Explore various leadership theories that should be considered in the age of artificial intelligence.

FOR DISCUSSION ABOUT SECTION 6,

These questions can be considered when looking at this major life transition and organizational transformation case study:

- What would be the possible results of creating AI Leadership Summits in every major country's community to explore the future and to develop plans to collaborate?
- How can we create AI Leadership Summits?
- Who should fund this transition of jobs to businesses and retraining for more jobs?
- What do we want our whole world to look like in the in the next 5 to 10 years?
- What are the action plans that you would recommend building the opportunities?
- What should people expect in terms of the length of time to smoothly transition through this major change for collaboration?

WEEK(S) 6 AND/OR 8

COURSE OBJECTIVE (COS)

CO 6: Evaluate organizational changes and challenges that can occur as a result of digital transformation.

FOR DISCUSSION ABOUT SECTION 6,

These questions could be used during Week 6 or 8 in the Live Discussion or in the Online Discussion by posting this case study as a supplementary case to review for a mid-week faculty submission.

Possible questions to consider around this major life case study are embedded in Section 6:

- What could help leaders explore the future to collaborate using AI between organizations or within organizations?
- What stops leaders from collaborating rather than competing in the development of AI?
- How could AI enhance or speed up the transition to collaboration?
- How can AI implementation be used to create a future where everyone wins?
- What are the criteria needed to create a better future?
- What is needed to bring over 95% of the people through the transition of AI as an associate in our future?
- What will keep our humanity's best characteristics alive and active?
- What do you want to see as our reality for the whole world in the next 5 to 10 years?

BEYOND COMPETITION PARADIGM DEVELOPMENT WITH THE LIMITED USE OF AI
Copilot was used to reorganize sections with applicable headings and to summarize the introduction from my writing.

Perplexity and Chatgpt were used to do research for literature review.

This paper was generated on my private computer from my reflections, travel experiences, and research, then transferred to a DVU computer.

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FACULTY-STUDENT COLLABORATIONS:

Navigating The Hype: Hybrid Projects Driven By AI Integration Efforts

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ABSTRACT

Projects are around us daily: new cars, skyscrapers, a neighborhood restaurant, and the latest video game, to name a few. Project managers and owners plan, budget, schedule, and execute these projects. Traditional project management styles will work for some projects, but the need for agility and fluidity is increasing, as is the subsequent need for new project management styles. As a result of AI integration efforts (such as chatbots, intelligent virtual assistants, and voice agents) of today's ongoing Traditional methodology-based projects, there is immense momentum behind Hybrid methodologies. Managing costs and schedules takes on new forms as well. Traditional project managers use indices to quickly assess where a project is and whether there is a need to adjust. Agile project managers, on the other hand, use a distinct set of matrices for those decisions. But is there one set of assessments a Project Manager could use for both kinds of projects? We argue that a unified set of performance indices can be used for a variety of projects.

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Keywords: project management, hybrid, indices, cost, schedules

INTRODUCTION

Can Traditional and Agile project management styles be used together as a Hybrid effectively or must they remain separate? This question can be reviewed and answered by looking into both styles and comparing their processes. The fast-changing business environment and the need to accommodate employees, vendors, and stakeholders are reasons that changes in project management styles may be better for some projects.

First, we address how both Traditional and Agile project management styles formulate the measurements used to determine the state of a project. All the indices that are used will be explained along with the calculations and how they are interpreted. The differences between the two systems and what criteria are used for each will be explained.

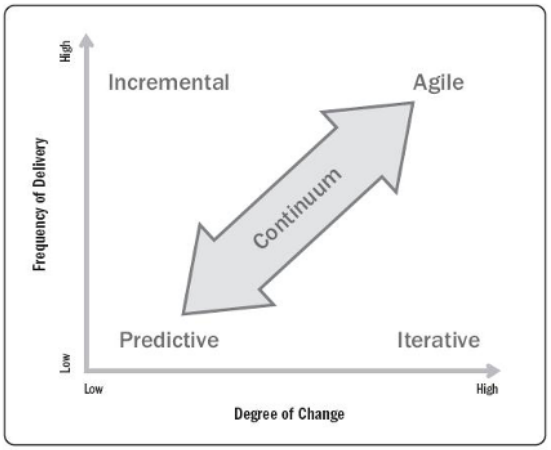
Understanding both styles and comparing the terminology will show the differences between them and what benefits both carries. This information will help us understand what type of organizations and what project types would best benefit from Traditional, Agile, or Hybrid styles, based on their indices to control costs and to schedule.

Second, we present a possible solution detailing the reason and justification for those choices. Providing several examples will also help clarify the differences in the systems and help us understand the need for both. Recommendations on the systems being used as a Hybrid will also assist in understanding the environment.

JUSTIFYING HYBRID METHODOLOGY

Methodology selection is heavily based on the nature of the project, rather than project manager's preferences. A Hybrid methodology is to be used when a project is not purely traditional and cannot be managed with a sole Traditional management methodology. From a technical standpoint, traditional projects are also known as predictive projects and are characterized by low tolerance for change, and accompanied by low frequency of deliveries, since there is only one scope. On the other hand, the Adaptive project, which is also known as Scrum, is the opposite. It lives by changes, which is a big differentiator, since it will not need any critical path, therefore no dependencies. As a matter of fact, as seen in ***Figure 1***, all non-traditional projects--Scrum, Incremental and Iterative--are more flexible in respect to change and/or number of scopes than their Traditional counterparts.

Figure 1 - The Continuum of Life Cycles



Source: *(PMI, 2017).*

To interpret with examples:

- Building a bridge would be a typical Traditional project, because there will be only one bridge (not half, not two). Also, the length of the bridge cannot be changed in the middle of the project
- Software development is a typical Agile project, because there will be endless deliveries in the form of new features. The need for change is the backbone of an Agile project
- Deployment (e.g. CRM) might make a typical Hybrid project, because any requirement which is not directly related to user screens may require a touch of a Traditional methodology. For instance, AI chat integration would need exploration, will have nothing to do with tasks (like user screens) as usual, cannot be managed with the existing SDL (Software Development Lifecyle), and will require process groups.

The need for a change in project management styles and incorporating a Hybrid project management system has become necessary due to changes in workplaces since the COVID-19 pandemic-imposed change. Organizations had to adapt throughout the shutdowns and create ways to continue tasks remotely. This change has brought to the forefront the issue of whether either Traditional, Agile or a Hybrid style would be better for Cost and Scheduling.

An article in the Harvard Business Review shows that "The most important concerns [business professionals] are raising fall under what is called the '5C challenges': communication, coordination, connection, creativity, and culture" (Haas, 2022). The challenges explained in the article can hinder projects and create an atmosphere of uncertainty.

It is also necessary to better understand specific details that stakeholders want updates on as well as quality issues that can be provided with an Agile system vs a Traditional system; the project's size and complexity make that determination. The size and complexity of a project are the key to understanding which style would be most effective and whether individual styles should be used or if both are used together as a hybrid.

Priority, Importance, and Time could create the conditions for a Traditional style with "well-defined scope and life-cycle phases where work is performed sequentially" (Kerzner, 2022). Each task is well-defined, and there are few changes made to the initial scope. Although projects under this style are delivered late, the structure may be necessary due to size and complexity.

Although structure and exact planning are helpful guides, they might not always be the best option for some projects. The freedom to be able to adapt to changes and modify execution and delivery throughout a project helps to ensure successful completion.

Compared to Agile styles, Traditional styles have many more factors that are becoming obsolete or are no longer relevant. Agile project management provides many more factors that have more positive outcomes and can assist in reducing failures and quality issues.

Uncertainty and irrelevant processes will always be present in projects, and the styles that are chosen to schedule will be picked based on the project's complexity and stakeholder involvement.

To transition successfully, organizations that currently use Traditional styles of project management would need to understand and gradually incorporate Agile methods (Kerzner, 2022).

Events in our society in recent years have forced organizations to look at their processes and implement changes to stay productive and complete projects in separate environments. These changes in procedures have created issues that will realign priorities and make some processes obsolete.

Hybrid-style project management systems appear to be less structured compared to the Traditional style due to the lack of scope and focus on completion dates. The differences between the two can be overlooked, and both could incorporate factors from each other that can improve their style.

PROBLEM STATEMENT

The fundamental challenge in project management is balancing cost and schedule while ensuring project success. Traditional methodologies like Waterfall and modern approaches like Agile offer distinct frameworks for managing these aspects.

EVM (EARNED VALUE MANAGEMENT) FOR TRADITIONAL

Indices are used in Traditional project management to evaluate the state of a project. Terms like Earned Value (EV), Planned Value (PV), Actual Cost (AC), Schedule Performance Index (SPI), and Cost Performance Index (CPI) are commonplace and are intertwined. The formulas for SPI and CPI and how they are connected are shown here. (Fleming & Koppleman, 2009).

- Earned Value (EV) = Budget at Completion (BAC) x % of work completed
- Planned Value (PV) = scheduled budget for completed work
- **SPI = EV / PV** (= 1 is on track, <1 is behind schedule, and >1 is ahead of schedule)
- Actual Cost (AC) is the actual dollars spent to a specific point in time to complete the work.
- **CPI = EV / AC** (= 1 is on budget, < 1 is over budget, and > 1 is under budget)

Most project management software calculates these automatically but understanding how they are calculated aids in the ability of a PM to use this data correctly. Understanding that when index calculations indicate below budget or behind schedule, a score closer to 1 is better. The decision to crash or fast-track a project begins with the SPI/CPI calculations and how they are interpreted.

EVM FOR AGILE

In Agile, there are often more people-centric metrics than numerical interpretations. As seen in Figure 2, terms like burndown charts, velocity reports, flow diagrams, customer satisfaction survey (CSAT), delivery speed, Net Promoter Score (NPS), Team happiness, and team turnover are often used. They tend to be more subjective than Traditional project management, but they do have value as Agile is a more customer-centric method (Almeida & Carneiro, 2023).

Figure 2 - Agile Metrics



Source: *Screenshot captured May 10, 2025 by E. Ozmen while logged into his personal Jira application via Atlassian.*

In an Agile environment, indices become metrics, but there is still Earned Value. While the quantity of metrics is larger than with Traditional project management, there are parallels. In ***Table 1***, the agile EV metrics are listed and defined.

Table 1 - Agile Earned Value Definitions

AgileEVM Metric	Definition
PSP (planned story points)	Total number of story points planned for this release
PW (planned weeks)	Total number of planned development weeks
BAC (budget at completion)	Total budget for the release
AW (actual weeks)	Number of development weeks elapsed to date
CSP (completed story points)	Number of story points completed to date
PPC (planned percent complete)	AW/PW
APC (actual percent complete)	CSP/PSP
AC (actual cost)	Total budget spent to date
PV (planned value)	Budgeted cost of the story points that were scheduled to be completed as of today; PPC * BAC
EV (earned value)	Budgeted cost for the story points actually completed as of today; APC * BAC
CV (cost variance)	Difference between planned budget and actual spend; EV – AC
SV (schedule variance)	Difference between planned schedule and actual time spent; EV – PV
CPI (cost performance index)	EV/AC
SPI (schedule performance index)	EV/PV
ETC (estimate to complete)	Based on current state, how much additional budget is needed to complete the release; 1/CPI * (BAC – EV)
EAC (estimate at complete)	Based on current state, what the total estimated cost of the release will be at completion; EAC = AC + ETC
Estimated time to complete	Based on the current state, the total estimated time needed to complete the release; 1/SPI * PW

Source: *(Nee, 2019).*

Using these definitions helps to understand the indices for a Hybrid project method, but the application may be harder.

As we said, traditional project management relies on metrics like Earned Value (EV), Planned Value (PV), Actual Cost (AC), Schedule Performance Index (SPI), and Cost Performance Index (CPI) (Lv & Wu, 2012). Agile methodologies emphasize metrics such as customer satisfaction surveys (CSAT), delivery speed, Net Promoter Score (NPS), team happiness, and turnover rates (Budacu & Pocatilu, 2018). The lack of a unified scope in Agile projects can lead to difficulties in applying metrics like SPI and CPI. However, adaptations such as using story points and sprints to estimate cost and schedule can bridge this gap (Yin & Li, 2014).

EVM FOR HYBRID

Finding a unified method for cost and schedule evaluations in Hybrid project environments is important for enhancing project management practices and integrating traditional Waterfall metrics with Agile's flexible and customer-centric

approaches. With such integration, project managers can achieve better resource allocation, improved decision-making, and more successful project outcomes. Continued research and adaptation of these methodologies will be essential as project environments evolve.

It is notable that a chicken-and-egg situation exists between the hype surrounding hybrid projects—driven by AI integration needs—and the AI-Enhanced Performance Index (AEPI) terminology, which aims to serve the increasing need for a unified performance metric.

The main points of pain can be summarized as follows:

- Definitions and Metrics: Traditional metrics used in Waterfall (e.g., Earned Value Management, Schedule Performance Index, Cost Performance Index) versus subjective, people-centric metrics in Agile (e.g., burndown charts, velocity reports, flow diagrams).
- Integration Challenges: Difficulties in combining these metrics due to differences in scope definition and project planning between Agile and Waterfall.
- Potential Solutions: Exploring Hybrid metrics that could provide a cohesive evaluation framework for both Agile and Waterfall projects. As noted, AEPI sets the trends through supercharged EVM, Predictive EVM, a.k.a. P-EVM or Normalized Velocity, for more proactive decision making.

APPLICATION AGENDA

Project progress is at the root of indices. In Traditional project management, there is a scope, a work breakdown schedule (WBS), and a budget that are all set at the beginning of the project. Agile, on the other hand, does not use these metrics. Instead, it uses sprints, story points, and burn-down charts to aid a PM in managing the project. It becomes obvious that there will be an issue when combining Agile with Waterfall for a Hybrid method. Table 1 illustrates that terminology is comparable. The key difference is scope. Its absence in Agile creates an undefined duration which is essential for SPI and CPI calculations. It becomes incumbent on the Project Management Office (PMO) to define how to correct for the lack of scope.

One possible solution is in Agile's use of backlogs, by thoroughly listing features based on the Project Charter or vision statement. Then assigning story points to the tasks a duration can be forecasted. The number of story points that can be completed in a sprint (team velocity) allows the PMO to estimate cost. The cost estimate plus the estimated duration puts a baseline in place. As story points and sprints are completed, the SPI and CPI can be calculated (Project Management Institute, 2017).

Another choice would be the use of an adaptive EVM metric using the agile earned value (AEV) formula. That formula is as follows:AEV = (BAC / total Sprints) x Sprints Completed x % of Sprint Goal Achieved.

Now, comparisons can be made. AEV - AC = agile cost variance (ACV) and has a basis to calculate CPI. The PM would have a numeric basis for any decisions for any alterations that might be necessary. A PM that is adept at Waterfall could now have some understanding of where a Hybrid project stands. This knowledge is a benefit for both the PMO and the organization.

To address the cost management and scheduling issues identified in the problem statement, we recommend adopting a Hybrid project management approach that integrates Agile methodologies with traditional Waterfall metrics, particularly Earned Value Management (EVM) techniques. This initiative will leverage the flexibility of Agile's iterative processes while maintaining the structured, measurable outcomes provided by EVM.

The relevance and significance of this recommendation is in its ability to bridge the gap between Agile and Waterfall methodologies, offering a cohesive framework that can adapt to dynamic project environments. As we highlighted in the problem statement, traditional Waterfall metrics such as Schedule Performance Index (SPI) and Cost Performance Index (CPI) are often rigid and lack the flexibility needed for modern, fast-paced projects. Conversely, Agile

metrics like customer satisfaction and delivery speed, though flexible, can sometimes lack the quantitative rigor needed for precise cost and schedule management.

Integrating EVM into Agile processes creates a Hybrid model that retains the flexibility of Agile while incorporating the structured measurement and control capabilities of EVM. This Hybrid approach will address integration challenges and enhance resource allocation, decision-making, and project outcomes.

MEASURING SUCCESS

Success will be measured through both lead and lag indicators:

- Lead Indicators: Early measures like team velocity and sprint completion rates that provide initiative-taking insights into project health and trajectory.
- Lag Indicators: Traditional EVM metrics such as SPI and CPI, offer a retrospective view of project performance against baselines (Budacu & Pocatilu, 2018; Lv & Wu, 2012).

By regularly reviewing these indicators, project managers can make informed decisions and adjustments, ensuring that both Agile flexibility and EVM precision are maintained throughout the project lifecycle.

RELEVANCE AND SIGNIFICANCE

This Hybrid approach is particularly relevant in environments where both Agile and Waterfall methodologies are used at various stages of the project. It addresses the core challenge of integrating different metrics and provides a unified evaluation framework. The initiative's significance lies in its potential to achieve the following:

- Improve Resource Allocation: By combining Agile's iterative planning with EVM's structured metrics, resources can be allocated more effectively, reducing waste and improving efficiency (Yin & Li, 2014).
- Enhance Decision-Making: The use of metrics from both Agile and Waterfall methodologies provides a clearer basis for adjusting, thereby reducing cost overruns and delays (Ghena & Ghiculescu, 2023).
- mprove Project Outcomes: By leveraging the strengths of both Agile and Waterfall methodologies, projects can be more adaptable and resilient to changes, delivering better products or services (Budacu & Pocatilu, 2018; Lv & Wu, 2012).

IMPROVED PROJECT MANAGEMENT PRACTICES

Integrating adaptive EVM with Agile methodologies enhances project management flexibility and control. This approach supports more informed decision-making and resource allocation, reduces risks of overruns, and ensures that projects are adaptable and resilient to changes. Such improved practices and delivery of better project outcomes and services, significantly result in project success rates (Budacu & Pocatilu, 2018; Lv & Wu, 2012).

CONCLUSION

Hybrid methodologies are becoming increasingly common. The business environment worldwide is moving faster and faster, requiring project managers to use systems that reflect the need for agility and quick transition. Agile and its subsets offer that. Even so, there is still a need for a Waterfall and the structure it brings to the project management field. The question until now has been how do PMs know where projects are when using Agile? The modified EVM numbers can provide a consistent look at the indices that PMs use to evaluate the health of a project.

As project management continues to evolve, so will the methods to evaluate a project. Indices are a staple in project management, and they will not go away. Instead, they will evolve as the industry does. As the methodologies have fused into a new Hybrid, the development of ways to calculate indices will be developed. It should also be said that as the industry and the math behind it grows, so does the software that powers the industry.

Change is inevitable; it is a part of life and business. The companies and individuals that change and grow fast will be the leaders going forward. Innovation for the sake of growth allows all to win. The future has endless possibilities for how project managers execute projects, and it will demand new and evolving methods to gauge their projects to keep them on time and within budget. With that change will come the need for project managers who are adept at the changing methodologies and the nuisances they bring.

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BOOK REVIEW:

A Neuroscientist Examines the Limitations of Using Education Technology

Horvath, Jared. Cooney. *The Digital Delusion: How Classroom Technology Harms Our Kids' Learning – And How to Help Them Thrive Again.* LME Global. August 2026. Pp. 336. Paperback $18.99. ISBN 978-8-218-88037-8.

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Technology has significantly impacted the delivery of education over the last century. Even before the introduction of the personal computer and the internet, many technological developments such as the radio, overhead projector, television, Scantron testing, and the calculator were integrated into the classroom to help facilitate instruction and enrich the learning experience. Of course, this is by no means an exhaustive list. In fact, our university owes its very existence to our founder, Herman DeVry, the inventor of the portable motion picture projector. Herman DeVry not only recognized the educational potential of motion pictures but also provided American schools with over 50,000 projectors and educational films to support that vision. His impactful and enduring contribution to education has been fittingly recognized by the Smithsonian Institution with some historians referring to him as the "Father of Visual Education."

In the latter half of the 20th century, a new era of the application of technology to education began with the "digital revolution" that advocated the integration of educational technology, or "EdTech," in nearly all aspects of instruction. Dr. Jared Cooney Horvath, a former educator turned neuroscientist, provides a critical review of the effects of the EdTech transformation in his recently published book *The Digital Delusion: How Classroom Technology Harms Our Kids' Learning – And How to Help Them Thrive Again.* He argues that, over the last two decades, significant declines in student academic performance and mental health throughout the developed world have coincided with the widespread adoption of EdTech. To support his argument regarding academic performance, Horvath cites twenty years of data from international assessments like PISA, TIMSS, and PIRL. These results from various countries consistently show a correlation between increased computer use and lower student achievement across subjects. Horvath argues that an over-emphasis with teaching specific technology tools has narrowed the scope of education. By prioritizing these tools over broader learning, schools may inadvertently limit students' cognitive development and their ability to adapt in the future. From a mental health perspective, Horvath believes that mental health has suffered due to the loss of empathetic relationships because "learning isn't just cognitive, but [also] deeply human" (p. 58).

With a publication date of 2026, a work of this nature would be incomplete without addressing artificial intelligence (AI). Horvath devotes two full chapters of the book to artificial intelligence. The author believes that AI has "opened a Pandora's box" of unknown, unintended consequences for education. As with most innovations, early adopters typically tend to be fervent supporters who give little, if any, serious consideration to unintended negative consequences.

Horvath details several ways AI could be harmful to learning. The first is what he refers to as cognitive "offloading." Over time, offloading tasks to a technology eventually creates a dependency. What an expert may consider as an efficiency-enhancing tool, a novice may view as a rationalizing excuse for expending little, if any, effort in acquiring the related knowledge or learning the applicable skill. As Horvath claims, "cognitive offloading isn't a shortcut to learning, it's a detour around it" (p.113).

Horvath also warns that AI may undermine learning by bypassing foundational knowledge. He argues that higher-order skills, such as applying, analyzing, and creating, as well as deep thought in most academic disciplines, depend entirely on a solid base of remembering and understanding. While AI excels at efficiency, boosting productivity is not a substitute for learning. True cognitive development and the capacity for higher-level thinking require acquiring foundational knowledge that a shortcut cannot provide.

Horvath also explains how AI could be very harmful to a learner's identity or sense of self-worth. He believes that we build our identity as individuals and learners through our struggle and efforts. Heavy reliance on artificial intelligence in education risks outsourcing this vital self-development process that is essential to answering the important questions of "Who am I?" and "How did I get here?". As the author warns, if educators are not careful, schools in the future may cease being institutions of higher learning and self-discovery and instead become merely training facilities where students are simply taught how to prompt a tool to do the thinking for them.

There is no doubt that technology has and continues to transform our lives. Resisting the adoption of new technologies has always been a futile endeavor. However, in education, with the benefit of hindsight, we often come to the realization that the initial enthusiasm we embraced for a technology's potential may eventually be more than offset by some of its unintended negative consequences. As an example, many parents and places of learning have begun banning cell phones, restricting social media, and limiting computer screen time. Only time will tell if we end up having similar second thoughts about the use of artificial intelligence.

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BOOK REVIEW:

A Spark of Excitement

Lewer, Dan. *Lectureless: Teaching History to Engage and Empower.* Dave Burgess Consulting, Inc. June 2026. Pp. 176. Paperback $27.00. ISBN: 978-1-968898-23-6

Shawn Schumacher,
College of Liberal Arts & Sciences

Reviewer Note: Shawn Schumacher, PhD, Senior Professor of English and Humanities at DeVry University, Lisle, IL

As an instructor of Humanities, I teach vital aspects of History, Literature, Philosophy, and Visual and Performing Arts. Over the years, like many Humanities educators, I have fought the stereotype of the dull, tiresome professor who drones wearily on through stale lectures with lackluster PowerPoint presentations, and who then typically assigns a textbook chapter reading and gives a test focused primarily on names and dates of events or assigns an essay based solely on an opinion-based topic, such as "What did you think of this particular piece?".

Seeking strategies to break this stereotype, I looked to Dan Lewer, a History instructor and curriculum developer, who has designed a compelling alternative for educators in his new book *Lectureless: Teaching History to Engage and Empower.* Through multiple models of research-based instructional practices, Lewer shares pragmatic, straightforward lessons that allow new and experienced teachers to bring their passion and subject matter expertise to the classroom. In his book, Lewer, who also provides teachers with story-based history videos with full lessons as a social media content creator, teaches educators how they can move beyond the lecture as the default mode of instruction and can cultivate an infectious energy in the classroom; doing so, as Lewer details throughout his book, results in a transformation that shifts learning from passive to active and disengaged to engaged.

Through his practical methodologies, Lewer describes how refocusing one's teaching away from the traditional lecture to making the past real and relevant can foster today's learners to become stronger critical thinkers, assertive problem solvers, and effectual agents of their own learning. In his book, Lewer keenly illustrates how learning about the Humanities helps students better understand the world today, contributes to solving future global problems, assists us in connecting to other people and cultures, aids us in gaining empathy and appreciation for global diversity, and inspires us to make a difference in the world.

Lewer's strategies to inspire educators to spark their students' curiosity in the Humanities begin not with lectures, but through constructive, powerful prompts which help students see the value and relevance of the Humanities. More specifically, as Lewer acknowledges, generating simple, open-ended questions on a topic such as the significance of Ancient Egypt to the modern world creates bridges to the present which can unlock possibilities for deeper exploration and discovery for reluctant or struggling learners. Moreover, Lewer provides a framework of active learning strategies that make the

historical aspects of the Humanities come alive; by crafting Story Lectures, as Lewer labels them, educators can relay personal stories that connect to the theme or topic of the lesson and can convey historical narratives with fresh, real-life characters that bring life to dry, fact-laced lectures.

Lewer not only also acutely uses primary sources to bring historical texts to life for his learners; but he also further details the need to spark engagement by applying what he calls "The Ken Burns Classroom Effect." Specifically, Lewer brings historical images to life in his presentations by panning or zooming across an image and by layering music into the background—music that may be from the actual historical period or music that simply fits the mood of the event or character. Lewer contends that since "music is at the heart of all the human cultures we study," music in the Humanities classroom is one of "the simplest and most powerful ways to pull students into the lesson and immerse them in the time or culture being studied" (p. 57).

Finally, in lieu of lectures, Lewer advocates for educators to foster deep, student-led discussions which emphasize the importance of academic dialogue in Humanities classrooms. Lewer points out, however, that these discussions must begin with community in the classroom, where students feel safe to engage thoughtfully and wholly, so they can build both academic success and confidence, while connecting with others through bold and courageous approaches to learning.

Dan Lewer's most recent book, *Lectureless: Teaching History to Engage and Empower*, affords educators the freedom to discard the traditional, teacher-centered lecture in today's classroom. By furnishing sound structure and support, Lewer intelligently demands diverse perspectives in the Humanities classroom through informal activities, such as immersive debates, Socratic seminars, and continuum discussions. As one who continuously strives to combat student disengagement and boredom in my own classroom, I find Lewer's book to be a breath of fresh air, as it is richly designed for educators to skillfully engage learners and to spark excitement and empowerment in the teaching of the Humanities.

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