AI-affordance alignment drives authentic learning gains without foundational erosion: Quasi-experimental evidence from an environmental data science course

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Highlights

1. Study offers quasi-experiment design isolating impact of a single GenAI upgrade
2. AI-affordance alignment (A3) links task, pedagogy, learner needs to learning gains
3. A3 improved GPT-4o cohort over GPT-3.5 on authentic tasks without exam impact
4. A3 shifted student help-seeking to autonomous and improved sentiment toward AI
5. AI upgrades will improve learning when paired with effective pedagogical design

Abstract

Grounded in self-regulated learning, we present a quasi-experimental design to examine how a generative AI upgrade affects learning in an upper-level Environmental Data Science course. We isolated the educational effects of an AI upgrade (e.g., from ChatGPT-3.5 to ChatGPT-4o) by keeping the curriculum, pedagogy, and assessments constant across two cohorts (Spring 2024, n=12 and Spring 2025, n=13). The comparison shows a significant gain in authentic, ill-structured project performance, no loss in AI-free foundational-exam scores, a shift from peer-dependent to autonomous help seeking and increased positive sentiment toward AI support. Our central proposition is that AI upgrades improve learning when paired with effective pedagogical design. Specifically, we advance the AI-affordance alignment framework where learning gains occur when AI capabilities are deliberately matched to task authenticity, self-regulated learning phase, and pedagogical goals. The findings, while limited by small sample size, single-site design, and a focus on performance rather than direct measures of critical thinking, suggest that advances in AI can improve higher-order performance without eroding foundational knowledge, provided that effective pedagogical strategies for AI integration remain in place. These strategies include process transparency, scaffolded AI use, hybrid AI-resistant assessment checkpoints, metacognitive reflections, and active instructor mentoring. The study provides guidance for integrating current and future advances in AI into higher education, especially in research-based contexts where there is a need to balance innovation with the preservation of learner agency and academic integrity. Future research should directly investigate the impact of AI upgrades on student critical thinking and cognitive development.

Keywords: Generative AI; future of higher education; self-regulated learning; help seeking theory; cognitive offloading; authentic assessment; affordance; environmental data science

Impact statement

Advances in generative AI are constantly shifting the higher education landscape, requiring pedagogical research and practice to evolve with the AI growing capabilities. To move from reactive adaptation to a strategic design, we propose that pedagogical design is a key constant that transforms the "moving target" of AI advancements into a predictable opportunity for enhancing learning, especially authentic learning. This work presents a quasi-experimental study that offers a controlled test of how an upgrade in generative AI affordances reshapes learning in higher education since the AI boom in late 2022. For a research-based higher education course, by holding pedagogy constant while AI capabilities evolved for two cohorts in Spring 2024 and Spring 2025, the study uniquely isolates the impact of AI advancement on learner behaviors and outcomes. Our findings show positive convergence where students produce significantly better work on complex projects without eroding their foundational knowledge, accompanied by a positive shift in behavior toward autonomy and overall positive sentiment. We propose that the educational outcome of using AI is not determined by technology alone, but by embedded pedagogical design. Accordingly, we advance the AI-affordance alignment framework, offering practical design principles for scaffolding AI use, promoting self-regulated learning, and redesigning assessments to support authentic learning. More generally, our findings contribute to an impending pedagogical pivot where AI as a co-teacher can absorb lower-level learning objectives, freeing instructors to mentor higher-order inquiry and creative synthesis. This work provides actionable guidance for educators to navigate the integration of current and future advances of AI into higher education. This is to preserve learner agencies, and empower learners with transferable competencies that will endure in an AI-driven future.

1. Introduction

The integration of generative artificial intelligence (AI) into higher education is rapid across science, technology, engineering and mathematics (STEM) and non-STEM disciplines in response to rising employer demand for AI skills and a broader workforce shift toward automation (Gilreath, 2025). However, this integration has multifaceted and often paradoxical impacts on education (Dergaa et al., 2024; Jose et al., 2025; Lim et al., 2023; Valcea et al., 2024) on hand, and is evolving on the other hand (S. Xu et al., 2024). On one hand, there is an ongoing debate about AI potential to support learning processes and scaffold learner development, and the risks of foundational knowledge erosion, critical thinking diminishing, cognitive atrophy, and new ethical dilemmas(Fu & Weng, 2024; Han et al., 2025; Klimova & Pikhart, 2025; Kosmyna et al., 2025; D. Lee et al., 2024; H.-P. (Hank) Lee et al., 2025; Melisa et al., 2025). This tension is evident, for example, in computation-integrated education. For instance, Yilmaz & Karaoglan Yilmaz (2023) find that using AI tools improves student computational thinking skills, self-efficacy, and motivation, while Groothuijsen et al. (2024) report that AI use can lead to declining code quality and a negative impact on student collaboration. Another concern is that the proficiency of AI in lower-level tasks could deter early-stage learners from developing the foundational knowledge essential for higher-order thinking (Valcea et al., 2024). This can potentially cause cognitive decline (Kosmyna et al., 2025), if AI use is not carefully managed (Dergaa et al., 2024; Gerlich, 2025; Lijie et al., 2025). Additionally, this can potentially lead to superficial understanding if AI is used to replace rather than supplement genuine learning efforts (Fu & Weng, 2024; Tan & Maravilla, 2024). On the other hand, the educational impact of AI is not static as it is continuously shaped by the rapid evolution and upgrades of AI tools, offering increasingly mature capabilities (Lee et al., 2024; Lubbe et al., 2025). For example, between early 2024 to early 2025, generative AI tools advanced from mainly conversational assistance to a collaborator that is context-aware with native multimodality, larger context windows, and dynamic web search. This can alter student learning processes, help-seeking behaviors, and performance on different types of academic tasks (Jose et al., 2025; D. Lee et al., 2024; S. Xu et al., 2024). These advancements are creating a moving target for pedagogical research and practice, who are continuously adapting to AI growing capabilities (D. Lee et al., 2024).

This dynamic and rapidly evolving context indicates a gap in literature that is the lack of experimental evidence on how generative AI affordances produce differential gains in performance, especially in authentic versus foundational task performance. The adoption of AI in higher education is rapid (Nevárez Montes & Elizondo-Garcia, 2025). Recent meta-analyses (Dong et al., 2025; Heung & Chiu, 2025; J. Wang & Fan, 2025; Youssef et al., 2024; Zhu et al., 2025) confirm a positive effect of AI on learning, yet these studies also report high heterogeneity, indicating that outcomes vary widely by context, domain, and the specific AI tool used. Accordingly, systematic reviews (Xia et al., 2024; W. Xu & Ouyang, 2022; Zhu et al., 2025) highlight the need for more empirical designs as the evidence on AI impact on learning outcomes remains limited particularly from controlled comparative studies in STEM disciplines. More critically, current research often treats generative AI as a uniform entity, failing to isolate the effects of specific, rapid upgrades in AI capability (Cai et al., 2024; N.

Wang et al., 2024). This is a critical gap given that the learner performance and behavior will evolve with AI technology, as this study shows.

To address this gap, this study examines the effects of the advancement of AI capabilities on learning outcomes through self-regulated learning theory (Zimmerman, 2000). We propose that the learning outcomes depend on the AI affordance alignment that is the fit between AI capability, the task authenticity, and the self-regulated learning phase of the learner. Improved AI capabilities can reduce the procedural load during the performance phase of authentic projects, freeing cognitive resources for higher-order reasoning. However, if the same tools are introduced prematurely, this could short-circuit schema formation with respect to foundational knowledge (Khlaif et al., 2025; N. Wang et al., 2024). Reports of students bypassing conceptual struggle for ready-made answers reinforce this risk (Gerlich, 2025; Kosmyna et al., 2025; Lijie et al., 2025). We therefore propose that pedagogical design and not the tool alone determines whether AI benefits outweigh risk. Specifically, while an advanced AI tool provides the capability to enhance student performance, it is the pedagogical design that directs that capability toward authentic learning gains while mitigating the risks of foundational erosion.

To test this proposition, we implemented a two-cohort quasi-experiment design in an upper-level Environmental Data-Science course in Spring 2024 (n = 12) and Spring 2025 cohort (n = 13) where instructor, syllabus and assessment were held constant and AI toolset varied. We compared cohorts on graded performance in authentic semester projects versus AI-free foundational exams, ranked help-seeking preferences, and affective responses captured through sentiment-coded reflections. By isolating the effects of a specific AI upgrade in a controlled setting, our study directly responds to calls for experimental designs that can establish clearer links between AI affordances and learner behavior (Belkina et al., 2025; Zhao et al., 2025). Thus, this study provides one of the first controlled, theory-driven tests of AI-affordance alignment in higher education. By examining how the intentional alignment of AI and pedagogy can transform student learning, this study contributes to the literature on balancing the benefits and risks of AI for shaping the future of higher education (Al-Zahrani & Alasmari, 2024; Cai et al., 2024; Lim et al., 2023; O'Dea, 2024; Yusuf et al., 2024).

2. Theoretical framing

This section establishes the conceptual basis for our central proposition of an AI-affordance alignment framework. We build this framework by integrating four key concepts, which are self-regulated learning (SRL), help-seeking theory, cognitive offloading, and authentic assessment. This aligns with an impending shift in higher education toward hybrid human-AI co-regulation, where the AI acts as a partner to scaffold learner SRL (Molenaar, 2022). While this study focuses on the performance phase of SRL, the role of AI in the full SRL cycle is discussed to provide context.

2.1 Self-regulated learning in the AI era

According to SRL, learning in not a passive process, but rather an active self-direct process (Panadero, 2017). The personalized learning environment provided by AI can enhance SRL

(Lin & Chang, 2023) including providing real-time scaffolding for SRL strategies than can lead to improved learning (Li et al., 2025). SRL involves learners actively managing their learning through a cycle of forethought, performance, and self-reflection (Zimmerman, 2000). SRL can be used to understand how learners engage with external tools like generative AI (Wang et al., 2025). In each phase, learners have distinct regulatory needs, which are cognitive, metacognitive, and motivational support (Panadero, 2017). To actively engage with learning, learners need cognitive support to process information, apply strategies, and critically analyze content (Alam & and Mohanty, 2024). To regulate cognitive processes effectively and develop adaptive learning behaviors, learners need metacognitive support to plan, monitor, and adjust their learning strategies (K. Wang et al., 2025). To promote long-term engagement in learning, learners need motivational support that improve their self-efficacy and positive self-talk, and sustain their effort even when the task is hard (Panadero, 2017).

How SRL needs are met in each SRL phase, determines whether AI will serve as cognitive support or a cognitive shortcut that undermines learning (Alam & and Mohanty, 2024; Gerlich, 2025). In the forethought phase, AI can assist learners with brainstorming, goal setting and planning, yet with risks such as relying on biased outputs, compromising originality, or lack of rigor (Chang et al., 2023). During the performance phase, learners execute their plans and monitor their progress. When AI capabilities are aligned with learner needs, it can support deeper engagement and cognitive agency (Wang et al., 2025). For example, AI can help a hydrology learner with code generation, data curation for a specific watershed, contextual geospatial technical details, and hydrologic meta-data of a stream in the study area. However, misalignment can promote passive consumption of surface-level solutions, displacing essential self-regulatory processes (Alam & Mohanty, 2024; Gerlich, 2025). For the self-reflection phase, learners evaluate their performance to adjust to future strategies. AI can support this phase through structured feedback, but only if critical review is encouraged rather than uncritical acceptance of AI outputs. However, if AI feedback lacks transparency or promotes over-trust, learners may bypass reflective judgment and default to superficial verification, which can limit the development of metacognitive insight (Zalazar-Jaime & Medrano, 2021). However, the learners' navigation of this cycle is not uniform. Some may resist using AI when it is misaligned with task goals (Khlaif et al., 2025), while others may actively regulate AI outputs to maintain their own cognitive agency. Similarly, engaging in critical review can be subject to individual learner personality traits (Weng et al., 2024). In any case, the goal of curriculum design in the AI era is to guard against executive outsourcing, where the illusion of regulation displaces genuine learning, as explained below.

2.2 Help-Seeking theory: From executive to adaptive AI help

Help-seeking is a key component of SRL. A key distinction exists between (i) adaptive help-seeking that is strategically seeking hints or guidance to overcome an obstacle while preserving autonomy and promoting mastery; and (ii) executive help-seeking that is seeking quick and direct answers undermining deep learning (Huet et al., 2016; Şahin et al., 2025). The instant, on demand, and judgment-free nature of AI responses can unintentionally blur the line between adaptive and executive help-seeking, potentially normalizing an answer-seeking behavior that bypasses metacognitive effort. However, the risk of executive help seeking behavior or executive outsourcing can be mitigated. We propose that authentic, complex tasks can redirect learners toward more adaptive help-seeking by shifting the focus from "correct answers" to a meaningful process. In this context, learners are prompted to use AI as a scaffold rather than a shortcut. Additionally, AI can lower social barriers to help-seeking, such as fear of embarrassment (Newman, 2002), encouraging learners who might otherwise hesitate (e.g., due to low confidence or high-performance anxiety) to seek assistance. As Msambwa et al. (2025) note, AI opens pathways for new, adaptive forms of help-seeking with non-judgmental guidance that aligns with learning goals. In the AI era, help-seeking needs to be reconceptualized to include not only interpersonal help (e.g., peers and instructors), but also strategic human-AI collaboration that can co-regulate learning and facilitate strategic cognitive off-loading.

2.3 Cognitive off-loading and scaffolding AI use

Cognitive offloading, which is the delegation of mental tasks to external tools (Risko & Gilbert, 2016), is central to how learners use AI (Gerlich, 2025; Iqbal et al., 2025). While beneficial for freeing up working memory for complex reasoning (Sweller et al., 2019), overuse risks dependency. On one hand, offloading can be highly productive. For example, by automating routine or extraneous tasks (e.g., code generation and debugging, or finding a specific dataset and metadata), AI frees up the learner working memory to focus on higher-order reasoning and germane cognitive load (e.g., learning a new technique or interpreting results) as suggested by Gerlich (2025). This study suggests that with improved AI affordances, this type of productive offloading can be enhanced during the performance phase of SRL. As such, cognitive offloading will reduce unproductive effort (extraneous load), while preserving learner agency in schema construction (germane load) according to cognitive load theory (Sweller et al., 2019). On the other hand, offloading can be risky. Uncritical reliance on AI for core learning process (e.g., idea generation, evaluation, or inference) risks creating epistemic dependency and accordingly undermining the development of metacognitive skills (Gerlich, 2025; Gonsalves, 2024) that are central to deep learning (Sparrow et al., 2011).

The pedagogical objective is thus not to prevent offloading, but to regulate what is offloaded and why. This is to ensure that AI remains a support rather than a substitute of core cognitive processes (Gerlich, 2025; Lee et al., 2025). A structured scaffolding approach for AI use is one way to manage this balance effectively. For example, Elshall & Badir (2025) and present study show progression from no-AI tasks to build foundational knowledge, to AI resistant assignments to introduce AI use, to structured AI use on complex problems, and finally to open AI use on authentic, ill-structured projects. This sequence is a mean to promote meaningful offloading and maintaining learner agency. Without scaffolded AI use, cognitive off-loading can be a low-effort cognitive strategy, particularly in open and high use of AI, where immediate and seemingly authoritative outputs can discourage deeper learning (Kim et al., 2025).

2.4 Authentic assessment: Aligning tasks with AI capabilities

The nature of the assessment is critical in the age of AI. The future of assessment lies not in banning AI, but in redesigning tasks to make meaningful learning the object of evaluation (Swiecki et al., 2022). For example, S. Xu et al. (2024) emphasize that using advanced AI such GPT-4o requires the design of sufficiently challenging tasks to support rather than replace human judgment and preserve academic rigor. We propose that the value of AI as a learning tool is most realized when applied to tasks that mirror real-world complexity. This is the domain of authentic assessment, which emphasizes complex, process-oriented tasks that require higher-order thinking and increasingly human-AI collaboration (Khlaif et al., 2025; Swiecki et al., 2022). Unlike well-structured problems with single correct answers, authentic tasks are often ill-structured and open-ended, and often compelling learners to define the problem itself before solving such as the term project (Elshall, 2025) of our quasi-experiment. Authentic tasks are essential in the AI era because they are resistant to complete automation. Instead, learners apply disciplinary knowledge in ambiguous and dynamic contexts that are not subject to complete automation (Perkins et al., 2024; Swiecki et al., 2022). This demands that learners learn to identify and critique, using AI not to replace their thinking but to augment their own intelligence and capabilities, thereby maintaining agency over their personalized learning (Ouyang & Jiao, 2021). Approaches like the AI Assessment Scale (Perkins et al., 2024), HEAT-AI (Temper et al., 2025) and FACT assessment (Elshall & Badir, 2025) provide frameworks for tuning the permissible level of AI engagement based on the learning goals, ensuring that AI is used to deepen rather than circumvent genuine learning. At the intersection of pedagogy and policy, these frameworks highlight the necessity of articulating AI affordances and constraints within assessment design (Khlaif et al., 2025).

2.5 Synthesis: The AI-affordance alignment proposition

Integrating the concepts of SRL, help-seeking, cognitive offloading, and authentic assessment, we advance the AI-affordance alignment framework in higher education. As shown in Figure 1, this framework posits that the educational value of generative AI is maximized when AI specific technological capabilities or affordances are dynamically aligned with pedagogical goals, task complexity, and learner regulatory needs. Such alignment ensures that AI affordances that serve as primary mechanisms for supporting skill development (Celik et al., 2024) are used to preserve learner agency and improve learner motivation. The key is to ensure that AI affordances serve as extensions of a learner cognitive strategies, not as substitutes that impair critical thinking and deep learning (Gerlich, 2025; Gonsalves, 2024; Jose et al., 2025; Lee et al., 2025). In complex, authentic tasks, this alignment is especially critical during the performance phase of SRL (Celik et al., 2024; Iqbal et al., 2025). When alignment is high, learners can productively offload procedural burdens to focus on higher-order reasoning, facilitating adaptive help-seeking. This turns AI into an epistemic partner or co-regulator (Gonsalves, 2024; Molenaar, 2022; Philbin, 2023) that augment learning rather than a tool for executive help seeking (Msambwa et al., 2025). This study provides an empirical test of this proposition, examining how a specific AI affordance, when aligned with an authentic project, improves performance without eroding the foundational knowledge as assessed through traditional means. Moreover, as shown in Figure 1, SRL is a cyclic process as the learning outcomes from one task do not represent an endpoint but feedback into the learner self-reflection and subsequent forethought. We further propose that AI-affordance alignment can additionally influence goalsetting for future tasks and sustained engagement (as observed in this study), creating a dynamic and evolving learning process (Figure 1).

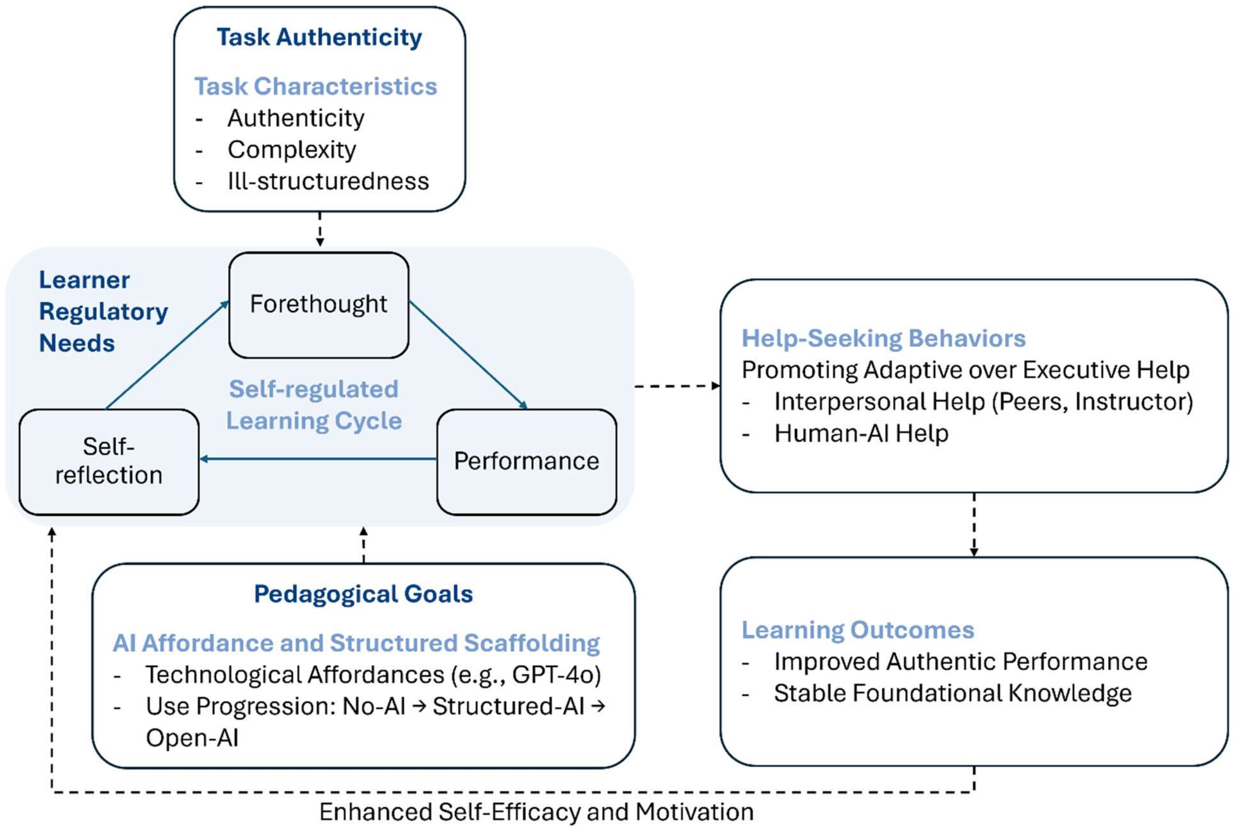

Figure 1. The AI-affordance alignment framework where matching AI affordances with task authenticity, pedagogical goals, and learner regulatory needs influences help-seeking behaviors and improves learning outcomes.

3 Methods

3.1 Study design

We employed a two-group, quasi-experimental design that compared consecutive offerings of the same upper-division Environmental Data Science course in Spring 2024 (n = 12) and Spring 2025 (n = 13). Both offerings used an identical syllabus, assessments, instructor, teaching assistant, contact time, and learning management system site. All instructional elements, including lessons, assignments, weekly milestones, and rubrics, were held constant. The key planned contrast was the generative-AI toolset available to students, which serves as the "AI upgrade" or treatment condition. The Spring 2024 cohort functions as the comparison group, allowing for inference on tool-related learning effects under otherwise stable pedagogical conditions.

3.2 Course context

The study was conducted in a course offered in a face-to-face format to a small cohort of undergraduate and graduate students from civil and environmental engineering and geoscience programs. With no prior programming prerequisites, the course introduces students to water, environment, and climate data analysis in Python. It is structured around project-based learning where students acquire datasets from sources like Copernicus, EPA, NASA, NOAA, USGS, and Water Atlas (of Flordа). The small class size of 12–13 students per cohort is an integral component of our design to enable individualized support and close collaboration with instructor and teaching assistant.

Over 15 weeks, the curriculum progressed through 10 themed modules, emphasizing hands-on practice. Foundational skills included Python basics, programming, and working with libraries such as Pandas for spreadsheet data, NumPy for scientific computing, and Matplotlib for visualization. Advanced skills involved workflows for multi-dimensional geospatial data using Xarray and CartoPy, machine learning for predictive modeling, and remote sensing with Google Earth Engine. The course is centered on a term project requiring students to identify and solve an environmental data science problem through data curation, visualization, and analysis. The course culminates in a comprehensive paper-based final exam. For more details, the course open-access textbook (Elshall, 2025) includes lessons, homework assignments, a semester-long project assignment, and final exam study guide. These core features were consistent across both the Spring 2024 and Spring 2025 cohorts, providing a stable instructional environment for comparison.

3.3 Course participants and baseline equivalence

To validate the quasi-experimental design, the baseline equivalence of the two cohorts was established at the start of the course. The instructor, with a background in groundwater hydrology, and the teaching assistant, with a background in software engineering, were the same for both cohorts. Prior programming experience, assessed via a first-day survey (detailed in Section 3.5), showed that both cohorts were dominated by novices (“none” or “a little” programming experience), and did not differ significantly (Figure 2a). Furthermore, Figure 2b shows a box-and-whisker comparison of homework scores completed without generative-AI assistance (Homework 1: Python basics; Homework 2: Python programming) pooled within each year (2024, $n = 24$; 2025, $n = 26$). Each box shows the middle 50% of the data with the inside line marking the median, the whiskers extending to the furthest values that are within 1.5 times the box height, and circles denoting outliers. The two groups achieved statistically indistinguishable scores on early homework assignments completed without AI (Figure 2b) as detailed in Section 3.5. A two-sample Welch test confirmed no significant difference in means ($p = 0.88$) or variances ($p = 0.78$) for these foundational scores. This comparability indicates that subsequent performance and attitude shifts can be attributed to the generative AI learning environment rather than baseline differences between the cohorts.

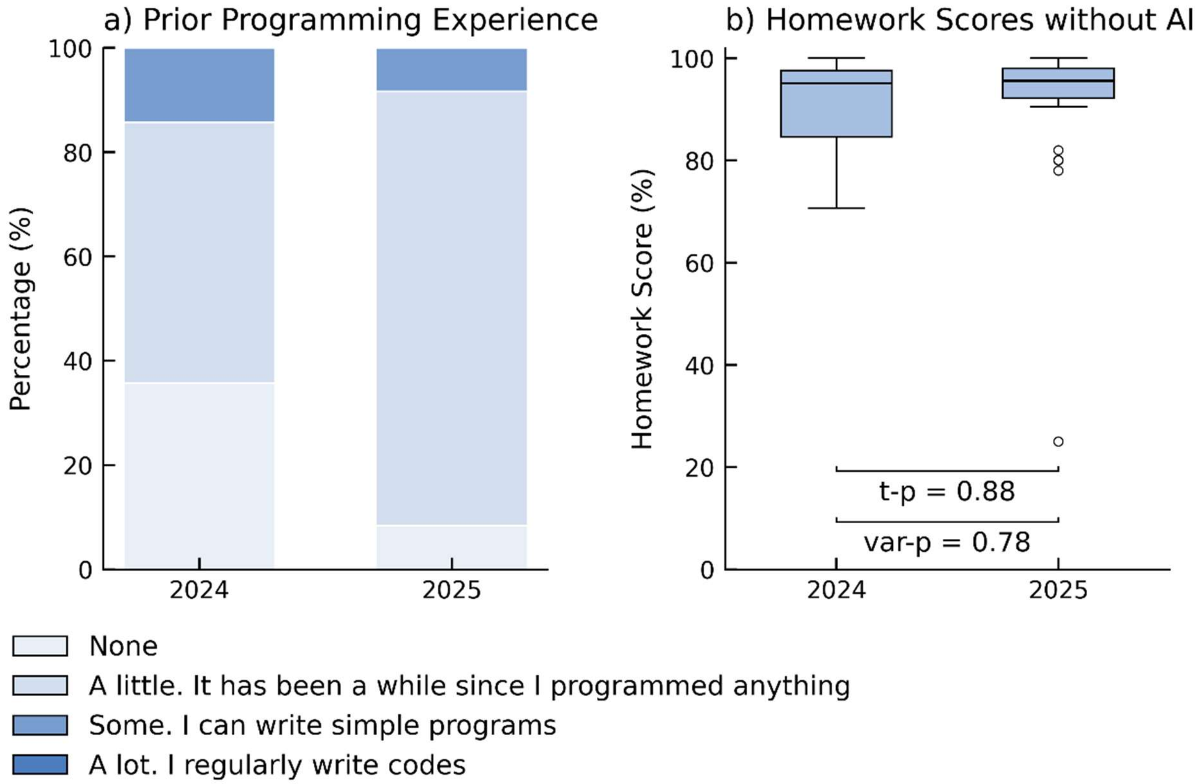

Figure 2. Baseline equivalence of the 2024 and 2025 cohorts. (a) Self-reported prior programming experience for each cohort (Spring 2024, n=12; Spring 2025, n=13). (b) Scores on initial homework assignments completed without AI assistance. The inset p-values from Welch t-test (t-p) and F-test (var-p) show no statistically significant difference in cohort means or variances, respectively.

3.4 AI tool upgrade from Spring 2024 to Spring 2025

To isolate the impact of rapidly evolving generative AI, the foundational toolset and core AI pedagogical policies were held constant for both cohorts. In both years, the integrated development environment (IDE) was Jupyter Lab with integrated Jupyter AI coding assistant. In-class demonstrations centered on ChatGPT as a primary example of a generative AI tool. Students were also introduced to other large language models via Chatbot Arena (2025) for comparing generative AI models. The course policy on AI usage was identical for both groups, providing a controlled baseline. The upgrade of generative-AI capabilities from January 2024 to January 2025 is marks a shift from conversational assistance to context-aware collaborator in environmental data science workflows detailed in Table 1. This upgrade involves key advancements such as native multimodality (e.g., text and image processing), larger context windows, and dynamic web search as well as progressive improvements in the core large language models.

A representative task from a student project analyzing the Caloosahatchee River watershed illustrates this transition (Duus, 2025). In early 2024, a student using ChatGPT 3.5 would be constrained by a static knowledge cutoff. The retrieval of a specific USGS Hydrologic Unit

Code (HUC) of the watershed or active monitoring station IDs near the Gulf of Mexico would be a manual process requiring external searching and experience. The 2025 toolset, featuring ChatGPT-4o with dynamic web-search, enables direct and accurate retrieval of this geospatial information. Subsequently, while the 2024 workflow required writing boilerplate Python code for data acquisition and processing with limited assistance, the 2025 toolset streamlines this by allowing file uploads and generating context-aware pipelines to download and format the discharge data. Furthermore, analysis and visualization, such as plotting watershed and station locations with GeoPandas and plotting discharge data, is transformed from a task requiring significant manual code adaptation in 2024 to an integrated process in 2025. In addition, the introduction of Jupyter AI v2.29 with contextual menus further enhances this workflow by providing cell-level code explanation and error fixing, a feature that was absent in the prior version (Jupyter AI v2.9). This progression allows students to focus more on higher-level analysis and interpretation rather than on the process of data retrieval and code implementation.

Table 1. Generative-AI tool capabilities in Spring 2024 vs Spring 2025 using ChatGPT as an example for generative-AI models and Jupyter AI as an example for AI coding assistants

Category	January 2024	January 2025
Core large language model	GPT 3.5 – Knowledge base: Static corpus (e.g., cutoff Sep 2021); Modality: text-only input/output; Features: No file upload; more prone to reasoning and code errors	GPT 4o – Knowledge base: Dynamic retrieval via integrated web-search including "deep search"; Modality: Natively multimodal (text, image); Features: direct file upload; markedly improved accuracy
Intra-session context window (memory)	A small (~4,000 token) context window resulted in contextual decay, necessitating frequent re-prompting to avoid errors in extended analyses	A large (~128,000 token) context window maintained high-fidelity context, facilitating sophisticated, multi-step analysis within a single session
Domain specific programming tasks	Required manual coding of boilerplate code for specialized tasks, such as NetCDF preprocessing (Xarray) or shapefile reprojection (GeoPandas)	Enabled context-aware pipelines for NetCDF workflows, geospatial reprojection and mapping based on direct file upload and live web data
Integrated data analysis environment	Python-based analysis tools were a premium feature (GPT-4) with limited support for basic file types such as CSV	GPT-4o enabled integrated Python execution with support for CSV, NetCDF, and shapefiles for in-chat processing, statistical analysis, visualization, and geospatial analysis
Accessibility	The free tier was limited to the base model (GPT 3.5). Access to advanced features like GPT-4 and web Browse required a paid subscription	Broader free-tier access to the advanced model (GPT-4o). Educational programs provided two-month extended access to premium features such as priority access during traffic and faster responses
IDE Integration (Jupyter AI)	Conversational assistance via a native chat user-interface in Jupyter Lab (v2.9 on Python 3.11) with limited direct code interaction	Cell-level assistance via contextual menus (v2.29 on Python 3.12) for debugging and refactoring, with enhanced code dependency awareness

3.5 Assessment and data sources

3.5.1 Assessment framework with scaffolded AI use

To evaluate student learning, we employed the FACT (Fundamental, Applied, Conceptual, critical Thinking) assessment framework, which differentiates between foundational knowledge without AI assistance, and performance on authentic tasks with AI assistance (Elshall & Badir, 2025) to balance AI-assisted and AI-resistant assessments. FACT assessment specific application to the course tasks is detailed in Table 2. This specific application is configured to attribute any gains to the ill-structured, authentic project (A), while establishing a stable, AI-resistant baseline for foundational knowledge (F and C). The project is considered "ill-structured" as it requires students to identify a research problem and execute a quantitative workflow that addresses a real-world challenge that lacks a single correct answer. In contrast, homework assignments are "well-structured," consisting of tasks with deterministic solutions where performance could be objectively measured.

Table 2. Application of the FACT assessment framework.

FACT components	AI permitted	Main task in this study
F – Fundamental skills	No	Homework 1-2 (coding without AI)
A – Applied, authentic work	Yes	Semester-long real-world project
C – Conceptual understanding	No	75-min closed-book written exam
T – critical Thinking	Yes	Multi-step case study (not analyzed here)

3.5.2 Performance metrics

Student performance was assessed across three categories: fundamental skill homework, an authentic project, and a final exam. All grade data were anonymized and coded with unique student identifiers. Fundamental skills (Homework) were evaluated using two assignments (Homework 1: Python Basics; Homework 2: Python Programming) for which AI use was not permitted. The assignments involved tasks with deterministic solutions, allowing for objective grading against a predefined answer key. To ensure grading consistency and inter-cohort reliability, both sets of homework were graded by the same teaching assistant for both cohorts. Grades were normalized to a 100-point scale and combined for comparison. With respect to authentic performance (Project), the capstone project requires students to complete open-ended, authentic tasks with open AI use. Undergraduate students need to work in a group of up to five students, and graduate students can work individually or in a group of up to four students. In 2024, out of the three graduate students, two worked independently. In 2025, out of the two graduate students, one worked independently. To mitigate the risk of "grader drift" between years and establish a reproducible grading standard, all projects from both cohorts were graded programmatically using GPT-o3 model. This advanced model is distinguished by advanced reasoning mechanism with self-critique that enhances consistency and accuracy (Guan et al., 2025). The model was provided with a detailed project rubric and evaluated each submission against the rubric. To validate this approach, the AI-generated rankings for projects were compared against the instructor's grades and found to be highly consistent. With respect to conceptual understanding (Final Exam), it was assessed via a 60-minute, paper-based final exam consisting of 60 multiple-choice questions. AI use was not permitted, and the same exam was administered to both cohorts to ensure a consistent measure of conceptual knowledge independent of AI assistance. The detailed instructions and rubrics for these homework assignments and project, and the final exam study guide are available in the course textbook (Elshall, 2025).

3.5.3 Survey instruments

Data was collected from two student cohorts: Spring 2024 (final n=12) and Spring 2025 (final n=13). Attrition was minimal, and the final survey response rate among enrolled students was 100% for both cohorts. Data was collected using an initial survey on the first day of class and a final survey at the conclusion of the semester. With respect to the initial survey, this "Get to know each other" survey was used to establish a baseline of the students' prior experience and included the question: "What is your programming experience?" (Figure 1). The end-of-course survey was the primary instrument for assessing student perceptions and learning behaviors related to AI. To maintain the integrity of the quasi-experimental design, only questions common to both cohorts were used for direct comparison. These included:

i. A five-point Likert-scale item on AI reliance: "When I solve an environmental data science problem, I heavily rely on AI?"
ii. A five-point Likert-scale item on learning difficulty: "After I study a topic in this course and feel that I understand it, I have difficulty solving problems on the same topic.
iii. A ranked-choice question on help-seeking behaviors: "When I get stuck on an environmental data science problem, rank how you seek help in order:"
iv. An open-ended prompt to capture qualitative data on student sentiment: "How has the integration of AI coding assistance, such as Jupyter AI or ChatGPT, impacted your learning experience in the course, both positively and negatively?"

The 2025 survey included several additional questions that are not used in this study but are available in the supporting materials (Elshall, 2025).

3.6 Data analysis

3.6.1 Sentiment analysis

The qualitative dataset comprised complete, open-ended responses from all enrolled students. For analysis, all responses were first anonymized, converted to lowercase, and stripped of punctuation. We then applied TextBlob v0.17.1, using its default Pattern Analyzer, to compute continuous scores for polarity ranging from -1 for negative to 1 for positive, and subjectivity ranging from 0 for objective to 1 for subjective. Following established practice, we classified polarity scores larger than 0.05 as Positive, less than -0.05 as Negative, and values in between classified as Neutral. For subjectivity, scores larger than or equal to 0.5 were labeled 'Subjective' and scores less than or equal to 0.5 were labeled 'Objective'. To verify the method reliability, a qualitative author review of the assigned labels was performed, confirming that this lexicon-based approach yielded a robust measure of student affective responses.

3.6.2 Thematic coding

To identify and quantify recurring themes within student reflections, we employed a hybrid thematic coding approach guided by Braun and Clarke (2006) reflexive thematic-analysis procedure. The initial codebook was deductively derived from themes in prior research on student-AI interaction in Spring 2024 (Elshall & Badir, 2025) and was then inductively expanded to capture emergent themes in Spring 2025. The source of this data was the complete set of student responses to the open-ended question on the final course survey. The unit of analysis was the individual phrase or sentence expressing a complete thought. Coding was conducted by authors who independently analyzed the entire corpus. Any discrepancies were resolved through discussion to achieve consensus. To quantify the evolution of themes, we calculated the percentage of student reflections in each year that contained at least one coded reference to each specific theme.

3.6.3 Help-seeking ranks

Data on help-seeking preferences were obtained from a question required on the final course survey where students were asked to rank six strategies from 1 (most preferred) to 6 (least preferred). For each of the six strategies, the mean of the ranks assigned by all students within a cohort was calculated. This procedure produces a single mean rank value for each strategy for each year.

4. Results and discussion

The presentation of the results follows the causal chain implied by the AI-affordance-alignment framework, moving from the technology upgrade (Section 3.4) to subsequent shifts in student behaviors (Section 4.1), their feelings and interpretations (Sections 4.2 to 4.4), their measurable authentic gains (Section 4.5), and finally, their sustained engagement (Section 4.6).

4.1 Behavioral shift from peer-reliance to self-reliance

The introduction of more capable generative AI tools in 2025 prompted a shift in student problem-solving behaviors from a reliance on peers toward greater self-sufficiency (Figure 3). In 2024, the top-ranked help-seeking strategy was "Seek help from classmates" (mean rank = 3.42), but by 2025 this inverted, with "Experiment on my own" rising to the first position (mean rank = 3.23) (Figure 3a). The preference for seeking help from classmates did not drop considerably, likely because students are encouraged to assist one another in homework and group projects. The most significant rank change was for "Consult online resources," which rose from the least-preferred strategy in 2024 to the third most-preferred in 2025. This suggests the AI enhanced web-search capabilities effectively directed students to useful, domain-specific online resources such as the Water Atlas of Florida, Capricious Climate Data Store, or the North American CORDEX data archive. The magnitude of these changes, quantified in Figure 3b, confirms the trend: “Consult online resources” and “Reach out AI” show the largest increases in preference (+1.21 and +0.65, respectively), while “Reach out instructor” saw the largest decrease (-0.41).

Figure 3c provides a visualization of this re-order between 2024 and 2025. The shifts signal students' increased trust in AI and digital information sources. The corresponding fall of

"Reach out instructor" to last place indicates a reduced inclination to interrupt the instructor as AI tools reduced technical barriers and became more capable and accessible. "Experiment on my own" rose to the top-ranked strategy suggesting increased autonomy. These changes suggest that students shifted from instructor-centered or peer-centered assistance toward more autonomous and AI-assisted strategies. These findings align strongly with the self-determination theory model validated by (Annamalai et al., 2025) such that our results provide behavioral evidence of this principle in action. Taken together, these results indicate a clear behavioral shift. With more powerful and reliable AI tools, students became more inclined to experiment independently and use online resources before turning to interpersonal help, demonstrating a greater sense of resourcefulness and self-efficacy. Annamalai et al. (2025) confirms that this autonomous behavior reflects increased competence.

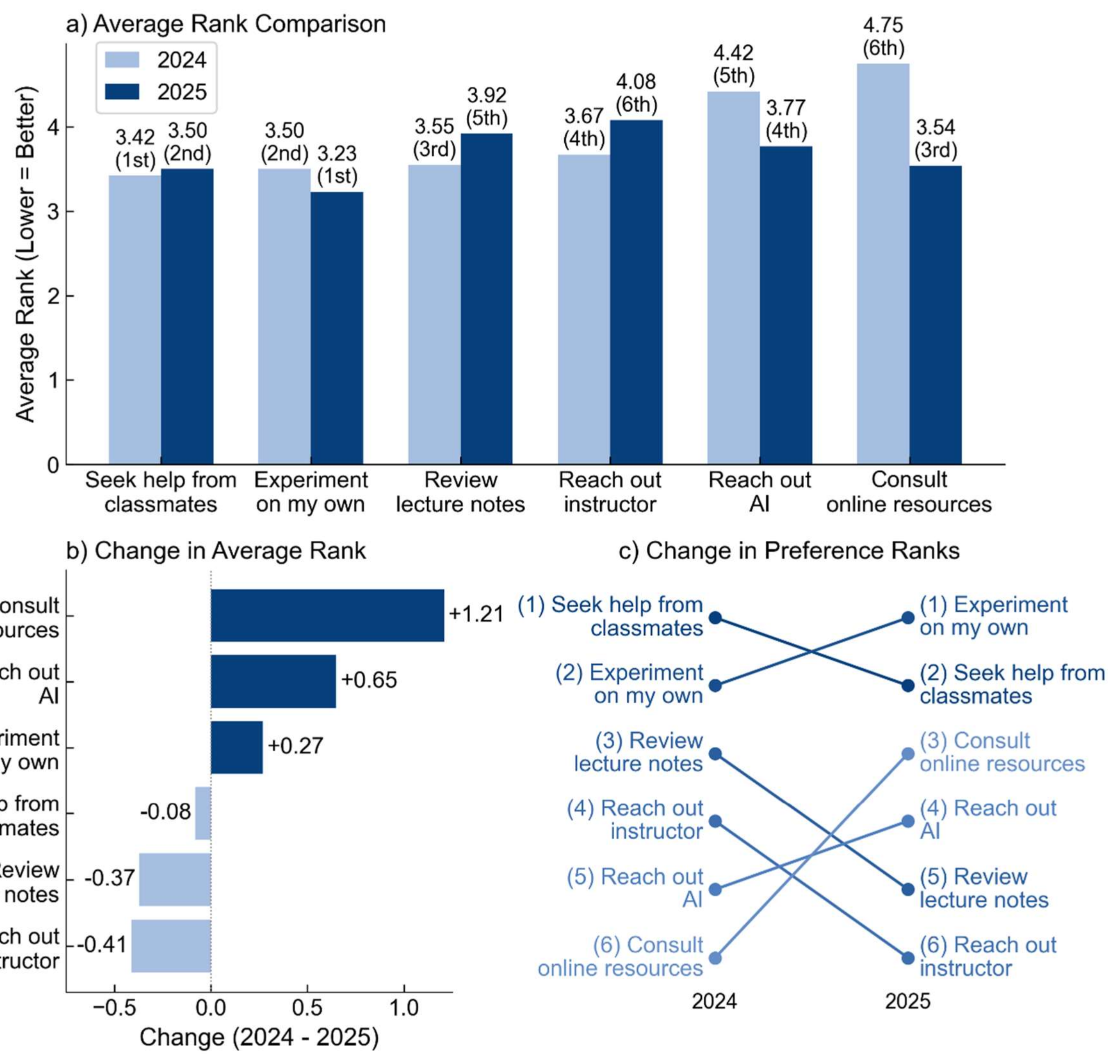

Figure 3. Evolution of student help-seeking strategies. (a) Mean rank for six strategies in Spring 2024 (n=12) and Spring 2025 (n=13), where a lower rank indicates higher preference. Numbers above the bars show the mean rank and the ordinal position for that year. (b) Year-over-year change in mean rank (2025 – 2024), where positive values signify a rise in

preference. (c) A visual re-ordering of the preference lists, highlighting the shift from peer-help toward independent learning and online resources, indicating greater self-efficacy and resourcefulness.

4.2 Increased reliance with reduced application difficulty

Following the shift in student help-seeking behavior, student perceptions of their relationship with AI also evolved, specifically concerning their reliance on the tools and the difficulty of applying their knowledge (Figure 4). The data shows that student reliance on AI increased with the upgraded tools (Figure 4a). In 2024, a combined 50.0% of students "Agreed" or "Strongly Agreed" that they heavily relied on AI. By 2025, this sentiment rose to a combined 69.3% (30.8% "Strongly Agree" and 38.5% "Agree"). This increase is an expected outcome, suggesting that as the tools became more capable and useful, students naturally integrated them more deeply into their standard workflow. This finding is strengthened by a simultaneous and significant reduction in students' perceived difficulty in applying knowledge (Figure 4b). When asked if they had difficulty solving problems on a topic even after feeling they understood it, the proportion of students agreed dropped from 41.6% in 2024 to just 23.1% in 2025. The plurality of 2025 cohort (46.2%) selected "Neutral" on this question, indicating a marked decrease in learning friction. Taken together, these two trends are revealing. More powerful AI tools led to greater reliance, but this increased reliance was correlated with students feeling more capable and finding it easier to translate conceptual understanding into practice. This suggests that upgraded AI provided productive support that improved, rather than hindered, student self-efficacy.

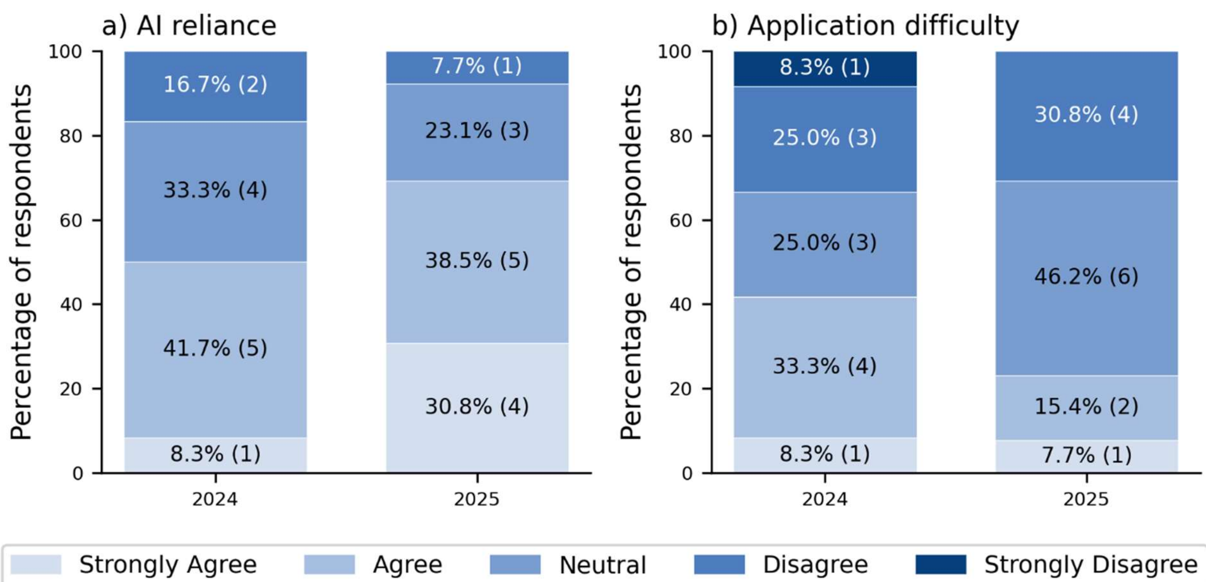

Figure 4. Student perceptions of AI reliance and application difficulty. Stacked Likert distributions for student responses from Spring 2024 (n=12) and Spring 2025 (n=13). (a) Responses to the statement: "I heavily rely on AI to solve environmental data-science problems." (b) Responses to the statement: "After I understand a topic, I still have difficulty solving problems on that topic." Percentages and absolute respondent counts are labeled within each segment. The increase in agreement on reliance paired with the drop in

application difficulty suggests that the upgraded tools promoted productive reliance that supported rather than hindered student understanding.

4.3 Affective climate from critique to endorsement

Beyond behavioral changes, the AI upgrade transformed the overall affective climate of the course. Affective climate, which refers to the collective emotional tone reflecting the group-shared feelings about their learning experience, shifted from cautious and objective to positive and introspective. An analysis of open-ended survey comments shows that in 2024, sentiment was mixed: 42% of comments were positive, while 25% were negative. By 2025, positive comments surged to 77%, while negative comments fell to just 8% (Figure 5a). A similar shift occurred in subjectivity. In 2024, comments were predominantly objective (83%), often consisting of technical critiques like "Jupyter AI was unhelpful because it did not work". In 2025, subjective or personal reflections became the largest category (46%), indicating students were offering more subtle evaluations of their personal learning process (Figure 5b).

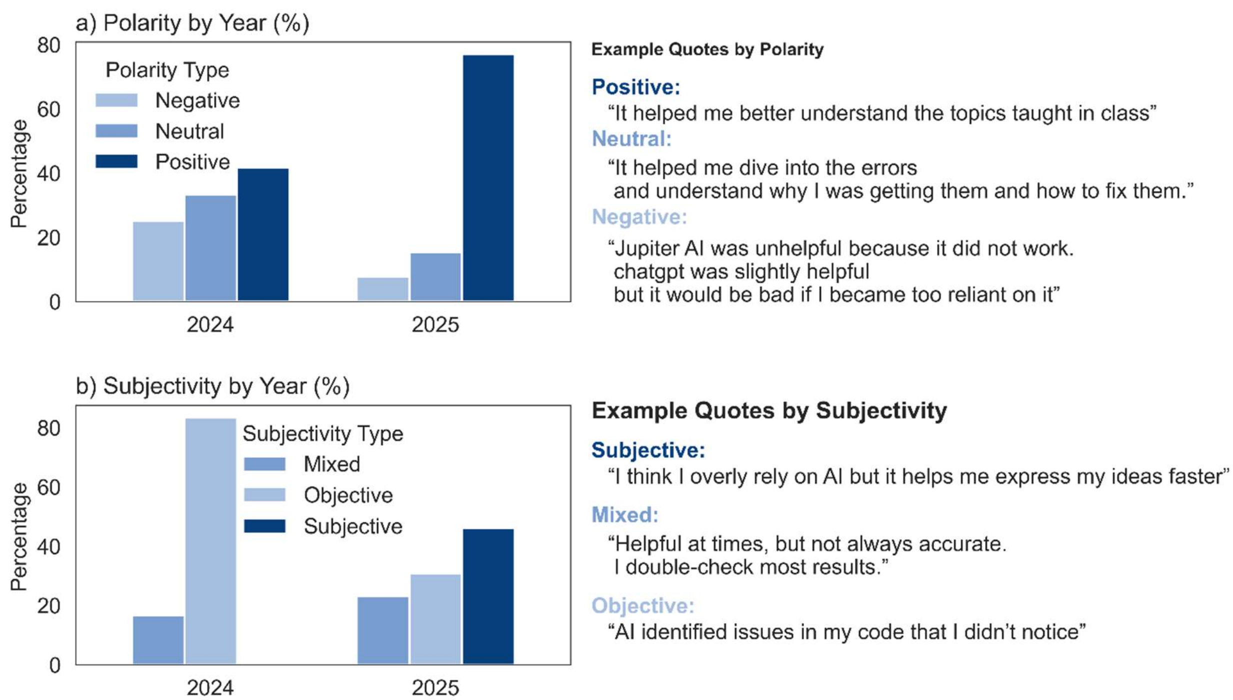

Figure 5. Sentiment shifts in student narrative feedback. (a) Proportion of coded student comments by polarity with example quotations for each category. (b) Proportion of coded student comments by subjectivity with example quotations for each category. Positive polarity increased, while subjective statements more than doubled, indicating richer personal reflections. The 2025 cohort talked about AI in markedly more positive and introspective terms, pointing to stronger engagement and ownership of learning.

A scatter plot of individual comments further visualizes this migration of sentiment (Figure 6). In 2024, most comments clustered in the objective quadrants reflecting reserved praise or technical critiques. In 2025, the comments shifted decisively into the "positive and subjective" quadrant, indicating strong personal endorsement. This combined evidence demonstrates that as the AI tools improved, students not only expressed more favorable opinions but also engaged in deeper and more personalized reflection about their learning. Students moved from simply stating whether the tool worked to describing how it shaped their understanding, a sign of greater ownership and engagement with the AI-assisted workflow.

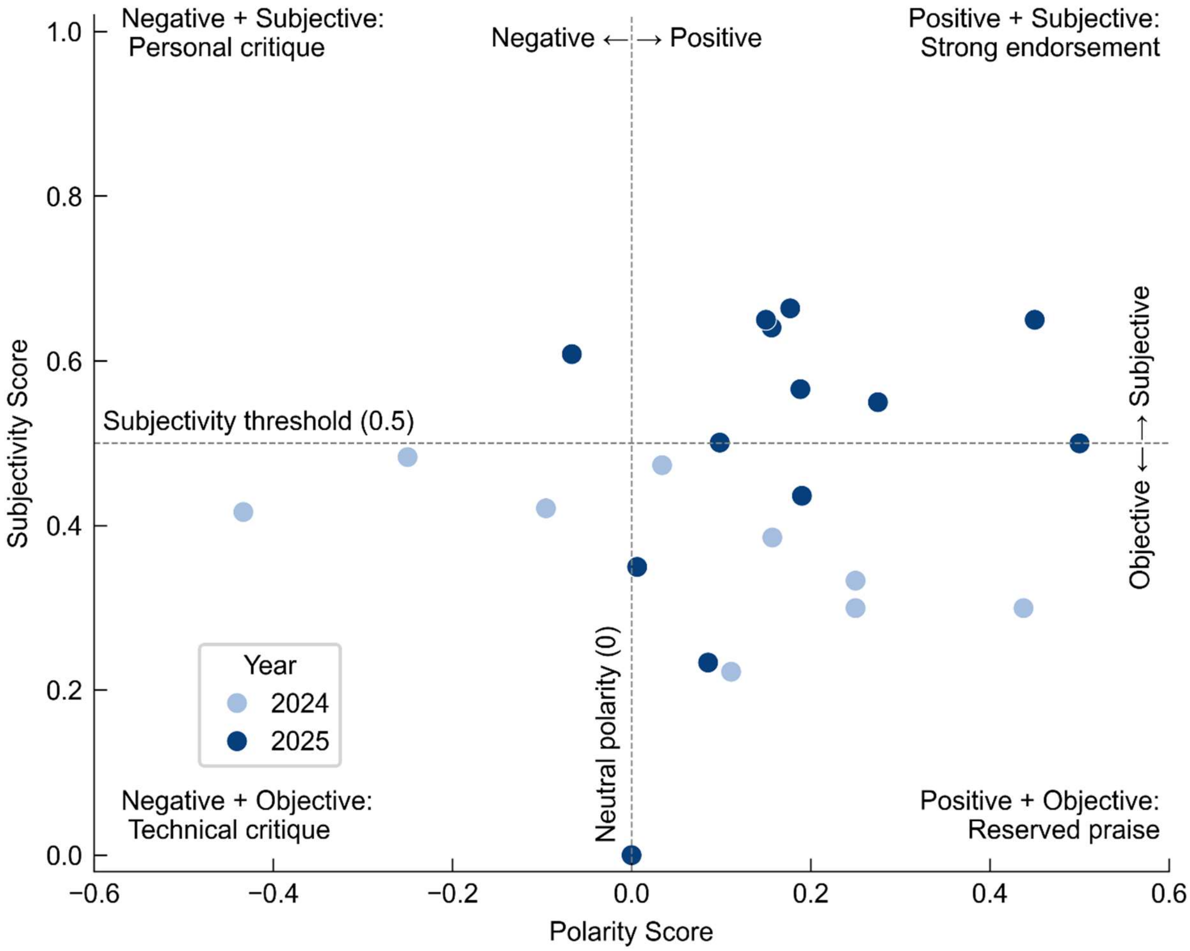

Figure 6. Polarity–subjectivity landscape of individual quotations. Each point represents a single student's comment, colored by year. The axes plot the comment polarity (negative to positive) and subjectivity (objective to subjective). The dashed lines partition the space into four interpretive quadrants, showing a clear migration of 2025 comments toward the "Positive + Subjective" quadrant. This migration indicates growing enthusiasm and ownership of AI tools.

4.4 Evolving themes: Independence versus overreliance

To understand the quantitative shifts in sentiment, a thematic analysis of student open-ended comments was performed. This analysis identified ten key positive and negative themes and tracked how theme prevalence changed from 2024 to 2025, as shown in the heatmap in Figure 7. The AI upgrade resulted in a clear evolution of student perceptions, with some benefits becoming more pronounced, some older frustrations disappearing, and new concerns emerging. The most significant positive shifts were in student perception of the AI role in enhancing autonomy and solving problems. The theme of "(+) Independence in Learning" saw the most increase, evolving from a minor theme mentioned by 16.7% of students in 2024 to a major one cited by 61.5% in 2025. This aligns perfectly with the behavioral shift toward self-reliance seen in Section 4.1. Furthermore, "(+) Support in Problem Solving" already the most common positive theme in 2024 (66.7%) became even more prevalent in 2025 (84.6%). This indicates that students found the upgraded AI to be an even more powerful and reliable partner for tackling complex coding challenges.

However, this increased capability was accompanied by a new set of concerns. The theme of "(-) Overreliance and Foundational Erosion" became more common, increasing from 16.7% in 2024 to 30.8% in 2025. A related, new concern also negative emerged regarding "(-) Superficial Understanding" (from 0% to 15.4%), with students worrying that the AI made it possible to get correct answers without deep understanding. At the same time, the AI upgrade appeared to solve previous frustrations. Critiques of "(-) Inconsistency in Performance" declined, and comments about the "(-) Gap in Addressing Needs" disappeared entirely in 2025, suggesting the new tools were more reliable and better aligned with the course's domain-specific requirements. Overall, the thematic analysis shows trade-off. The AI upgrade successfully enhanced student experience by providing more powerful support for problem-solving and prompting a greater sense of independence, while eliminating previous technical frustrations. However, this was balanced by increased student apprehension about the potential for overreliance and the risk of shallow learning, highlighting a critical tension for pedagogy in the age of advanced AI (Xia et al., 2024).

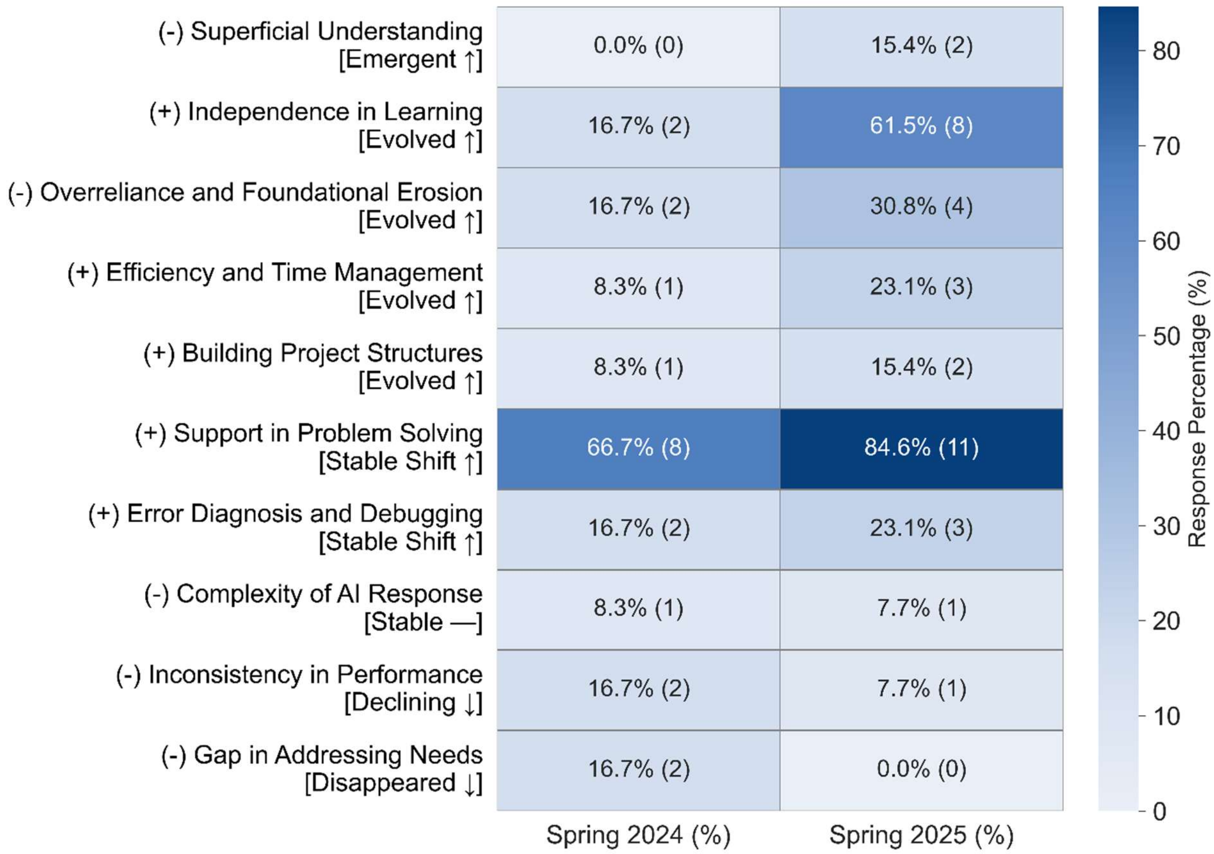

Figure 7. Thematic evolution of perceived AI impacts on learning. Heatmap of coded themes showing the percentage and number of student respondents mentioning each theme in Spring 2024 (n=12) and Spring 2025 (n=13). Arrows and annotations indicate the trajectory of each theme's prevalence: Emergent (↑), Evolved (↑), Stable Shift (↑), Stable (—), Declining (↓), or Disappeared (↓). Students increasingly credited AI with enhancing their independence and problem-solving skills, while concerns about overreliance grew and shallow learning emerged.

4.5 Project gains with stable foundational knowledge

The culmination of the preceding shifts in student behavior and perception is evident in the final performance outcomes, which were measured using the FACT framework to distinguish between authentic, AI-assisted work and AI-free assessments of foundational knowledge (Figure 8). The results show a significant improvement in project scores, supported by the stability of exam scores. Performance on the authentic, semester-long project, where AI use was permitted, improved significantly. The mean project score rose from 69.92 ± 6.27 in 2024 to 83.11 ± 6.99 in 2025, and a t-test confirms this difference is highly statistically significant ($p < 0.001$). Similarly, the median project score increased from 67.50 to 84.75, a difference that was also found to be statistically significant (Mann-Whitney U test, $p = 0.0004$). Levene's test showed that the variance between the two groups did not change significantly ($p =$

0.411). This indicates strong evidence that the upgraded AI tools enabled students to produce substantially higher-quality work on complex, ill-structured problems.

In contrast, scores on the traditional final exam, which assessed conceptual understanding and basic skills without AI assistance, remained statistically unchanged across both cohorts. The mean exam scores (66.81 ± 9.33 in 2024 vs. 64.10 ± 9.22 in 2025) were not significantly different (t-test, $p = 0.474$). Likewise, the median exam score was virtually unchanged (65.84 in 2024 vs. 65.00 in 2025), a difference that was not statistically significant ($p = 0.6426$). Levene's test showed that the variance between the two groups did not change significantly ($p = 0.455$). This stability is a key finding as it suggests that the significant gains in project performance were not a result of grade inflation or other confounding factors but were specifically linked to the upgraded AI-assisted workflow. Critically, this finding also indicates that the increased use of more powerful AI tools did not erode the student foundational knowledge. Together, these results demonstrate that the AI upgrade significantly improved applied performance on authentic tasks without compromising core conceptual understanding. This dual outcome is reinforced by comparative study (S. Xu et al., 2024) that found that GPT-4o significantly outperforms GPT-3.5 in solving complex mathematical problems, particularly those requiring multi-step reasoning, logical consistency, and code execution. The improved performance observed by S. Xu et al. (2024) provides a mechanism for the project score improvements in our 2025 cohort. The enhanced reasoning and coding capabilities of the upgraded toolset resulted in improved capability of tackling the ill-structured, authentic problems in our environmental data science projects.

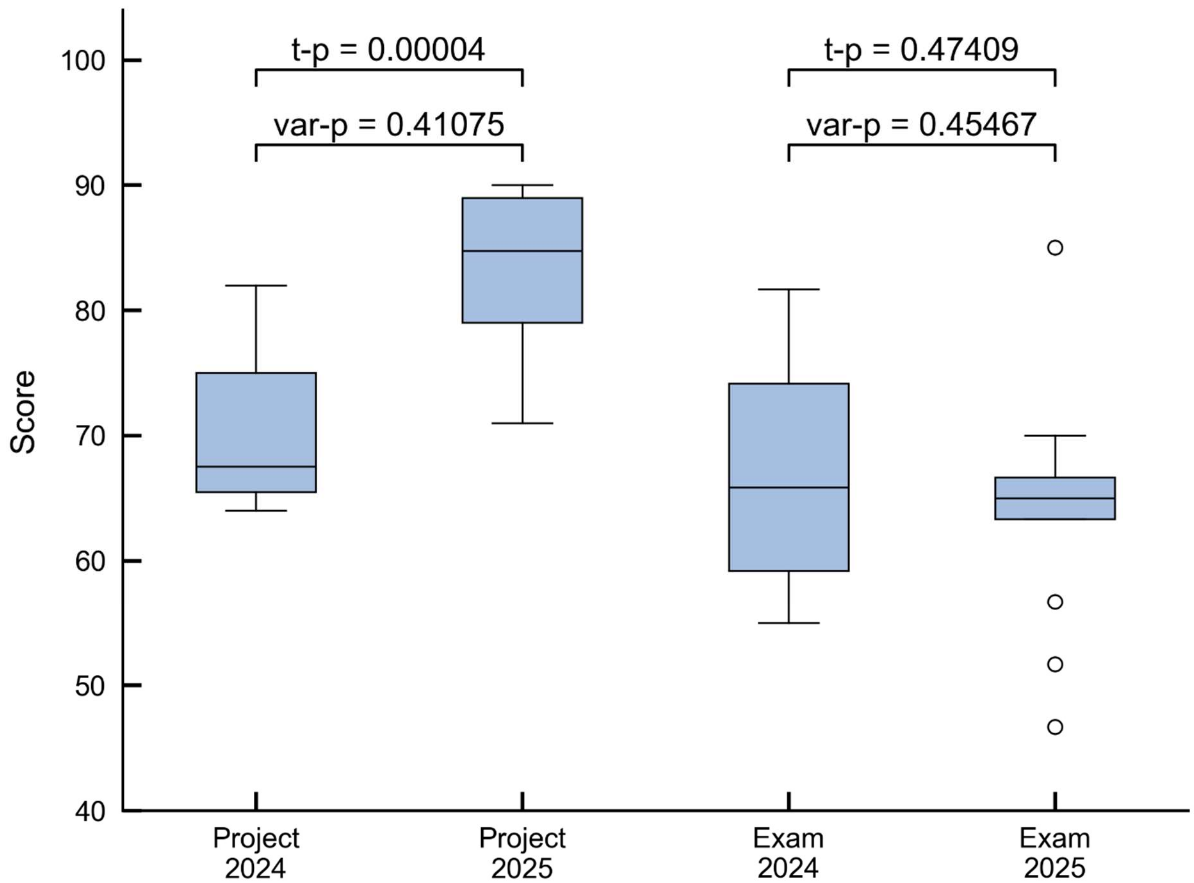

Figure 8. Student performance on project and exam scores. Box plots compare scores for the AI-assisted authentic project and the no-AI final conceptual and basic-skill exam across the 2024 (n=12) and 2025 (n=13) cohorts. Statistical annotations show the p-values for an independent samples t-test (t-p) and a Levene's test for equality of variances (var-p). The AI upgrade led to a statistically significant increase in project scores but no significant change in exam scores. This suggests the intervention improved applied performance without causing foundational knowledge to erode.

5. Synthesis and implications

5.1 Overview: An AI-affordance alignment interpretation

This study demonstrates that when generative AI is better aligned with the performance phase of SRL and embedded in authentic, ill-structured tasks, it can significantly enhance student learning outcomes without eroding foundational knowledge. This alignment of affordance, task, and pedagogy resulted in gains across performance, behavior, and affect. Across the 2024–2025 cohorts, a triangulated pattern emerged. First, students demonstrated behavioral realignment, shifting from peer- and instructor-centric help-seeking to AI-supported, self-reliant strategies. Second, this was accompanied by a marked improvement in the affective climate, with sentiment migrating from cautious neutrality to reflective endorsement. Third, these changes translated into measurable gains in applied performance, with statistically significant increases in project scores under AI-supported conditions, without erosion in conceptual exam outcomes. This dual outcome validates the alignment hypothesis. These results mirror what Cai et al. (2024) describe as the "differentiated impact" of AI where there is a gain in complex, authentic tasks but not in foundational skill assessments. Specifically, the students' increased ability to complete open-ended projects demonstrates a higher degree of epistemic agency, which is an enacted autonomy over the processes of problem framing, solution design, and knowledge construction (Damsa et al., 2010; Nieminen & Ketonen, 2024; Stroupe, 2014). At the same time, student stable exam scores confirm that foundational knowledge acquisition was preserved.

Importantly, the performance, affect, and behavior convergences do not seem like an incidental byproduct of AI upgrade, but a predictable outcome. Such combined gains are not unexpected when AI capabilities are aligned with the performance phase of SRL and embedded within authentic, ill-structured tasks. These gains can be attributed to scaffolding a range of cognitive and metacognitive processes simultaneously (Azevedo et al., 2022). Our findings thus suggest that students in 2025, equipped with more capable AI tools, engaged more autonomously by using AI as support rather than a surrogate (Annamalai et al., 2025). These findings align with emerging frameworks such as HEAT-AI (Temper et al., 2025) and the AI Assessment Scale (Perkins et al., 2024), which emphasize task authenticity and regulated AI use as key to safeguarding deep learning.

Moreover, student written reflections in 2025 exhibit greater personalized introspection. As seen in statements such as "AI allowed me to develop code and ideas far beyond my abilities" reflects not only an improvement in efficiency, but the emergence of AI as a co-creator of knowledge(Yuwono et al., 2024). Simultaneously, statements such as "AI made me comfortable with coding and data" reveal its function as a co-regulator, shaping confidence and cognitive strategy within the learning environment (Molenaar, 2022). In both cases, technology became more than a tool, it emerged as a co-creator and co-regulator within student learning environments, supporting the notation of human-AI partnership (Gonsalves, 2024; Jain et al., 2025; Philbin, 2023). Additionally, subjective ownership reflects what Tan & Maravilla (2024) identify as a transition from task dependency to competence-building support, fostering a sense of control and efficacy that enhances intrinsic motivation(Annamalai et al., 2025; Tan & Maravilla, 2024). This represents a shift from AI-directed learning where learner is recipient to AI-supported learning where learner is a collaborator, which is a need shift to finally move toward AI-empowered learning where learner is the leader (Ouyang & Jiao, 2021).

In addition, this intrinsic motivation extended beyond the course. three out of five final projects from the 2025 cohort are continuing into the summer, a leap not observed in 2024. In two cases, students were hired as research assistants and are now pursuing peer-reviewed publications on the use of machine learning to study marine harmful algal blooms (HABs) in the Gulf of Mexico and freshwater HABs in Lake Okeechobee, Florida. These collaborations, supervised directly by the instructor, suggest that AI affordances not only enhanced performance during the course but empowered students to take intellectual ownership of their work (Darvishi et al., 2024) and encouraged students to contribute to local issues and the broader scientific community (Roe & Perkins, 2024).

The results also suggest a pedagogical shift. As AI tools become more capable, instructors are no longer solely mediators of procedural knowledge. As AI becoming effective co-teacher (Niloy et al., 2025), instructor roles are being reshaped toward mentorship for higher-order thinking, guiding students in synthesizing data, interrogating uncertainty, and crafting analytical narratives. Recent studies confirm this shift, showing that AI enables instructors to focus less on content delivery and more on facilitating problem-solving and metacognitive engagement (Kim, 2024; Mollick & Mollick, 2024). This was evident in quantitative and qualitative shift in office hour dynamics, where students worked more closely and frequently with the instructor throughout their projects, and where questions evolved from predominantly syntax and debugging in Spring 2024 to study design and int in Spring 2025. Thus, the upgraded AI did not merely accelerate task completion, but more importantly facilitated a redistribution of cognitive load that encouraged students to experiment more freely. We summarize the causal chain of this study as AI upgrade, behavioral shifts, affective gains, authentic performance gains, and sustained engagement. Accordingly, the alignment of AI affordance with pedagogical purpose does not just result in significant performance improvements but also suggests transformational shifts in student learning behavior.

5.2 Mechanism of impact: Productive cognitive offloading

We propose productive cognitive offloading where students offload tedious procedural tasks (e.g., boilerplate coding) to focus on higher-order reasoning, analysis, and problem-framing. AI supported students by reducing extraneous cognitive load especially with procedural obstacles like debugging allowing for increased germane processing such as data interpretation and synthesis. This reflects predictions of cognitive load theory that learners benefit when effort is reallocated from routine execution to strategic reasoning (Sweller et al., 2019). Recent studies show that AI-supported learners exhibit higher-order integration and metacognitive engagement by fact-checking and challenging AI outputs (Essien et al., 2024), provided scaffolds like constructivist learning principles are in place (Kim et al., 2025; Tan & Maravilla, 2024). Students viewed AI as a partner or as one student reported “my AI friend” that accelerated troubleshooting, yet it is unclear if that deepened conceptual engagement. These findings align with Zhao et al. (2025) who argue that AI can function as a cognitive amplifier rather than a shortcut when embedded in pedagogical designs that encourage critical analysis and evaluation such as authentic tasks. On the other hand, Kosmyna et al. (2025) warn of cognitive debt where students offload core cognitive processes such idea generation and structuring, leading to weaker neural engagement and potential skill atrophy. However, it remains unclear whether regulating cognitive offloading through productive offloading could prevent the "cognitive debt" they warn against.

5.3 Behavioral shift: Toward resourceful self-regulation

Behaviorally, students shifted from reliance on peers and instructors to autonomous experimentation and AI-mediated support. This transformation aligns with SRL theory, which identifies adaptive help-seeking as a sign of increasing learner agency (Zimmerman, 2000). By providing on-demand support for technical challenges, the AI tool can satisfy learner core psychological needs for both competence (feeling capable) and autonomy (feeling in control), which are key drivers of intrinsic motivation to use AI for learning(Annamalai et al., 2025). Thus, as external tools, AI provides the needed support to help learners tackle challenges (e.g., coding minutiae and debugging) just beyond their current abilities, especially when they are still developing fluency in complex domains (Chang et al., 2023; W. Xu & Ouyang, 2022). This support structure operates within what Vygotsky (1978) termed the zone of proximal development, which is a gap between what a learner can do alone and what they can achieve with guidance. As a result, AI alters the help-seeking sequence, empowering learners to resolve technical issues independently before engaging peers or instructors for higher-level conceptual questions (Hou et al., 2024; W. Xu & Ouyang, 2022) especially due the on-demand nature of AI support with minimal social cost (Hou et al., 2024).

5.4 Affective climate: Empowerment with caution

Affective responses evolved as AI tools matured. This shift is consistent with broader findings that student engagement increases when AI is perceived not merely as a utility, but also as a learning partner (Cai et al., 2024). In 2024, student sentiment was mixed, often fixated on tool functionality. By 2025, responses were not only more positive, but more reflective and self-aware. Students frequently described AI as reliable, empowering, and essential, echoing patterns observed in other studies where AI enabled greater comfort with complex tasks and improved motivation (Dai, 2024; Ilieva et al., 2023). While many described AI as empowering and efficient, several also voiced concerns about overreliance or diminished effort, what Jose et al. (2025) call the “cognitive paradox” of AI. Specifically, Jose et al. (2025) argue that cognitive offloading to AI risks weakening metacognitive engagement, especially when learners lack the maturity or instructional support to critically vet AI outputs. This dynamic was mirrored in students' fears of "superficial understanding" and "undermined foundational skills", a concern that emerged from 0% in 2024 to over 15% in 2025. These findings align with warnings that overdependence on AI can diminish long-term retention and learner confidence (Wilson & Nishimoto, 2024) and lead to cognitive atrophy (Kosmyna et al., 2025). Either way, this blend of enthusiasm and critique suggests learners are not naïve adopters but are beginning to develop what Jose et al. (2025) call "AI fluency", which is the discerning ability to engage AI with both appreciation and epistemic caution. Such discernment is critical for long-term learning and emphasizes the importance of preparing ethical and self-regulating learners, who can robustly navigate the double-edged affordances of AI in education (Cai et al., 2024; Chang et al., 2023). Yet developing such discernment is not uniform across learners and is function learner personality traits, requiring strategies for supporting different SRL phases (Weng et al., 2024)

5.5 Outcome pattern: Authentic gains without foundational erosion

Statistically, students in the AI-upgraded cohort significantly outperformed peers in authentic project work while maintaining similarity on AI-free, foundational exams. This dual outcome supports early findings by Elshall and Badir (2025), who argue that well-aligned AI tools can enhance applied performance without diminishing core understanding. Similar hybrid gains are reported by (Awadallah Alkouk & Khlaif, 2024), who recommend bifurcated assessment models to preserve academic rigor while embracing AI affordances. These findings directly challenge warnings of conceptual decay (Wecks et al., 2024) offering evidence that erosion is contingent on AI-affordance alignment with learning needs, course design, and task characteristics. This study underlines the potential of AI not as a threat to foundational knowledge (Celik et al., 2024; Essien et al., 2024; Zhao et al., 2025). Rather AI can improve for authentic learning gains (Cai et al., 2024; Elshall & Badir, 2025), provided AI use is bound by rules, scaffolded to provide structured support within these rules, and aligned to ensure that the rules and support match the learning goals.

5.6 Theoretical implications: Rethinking executive help

Traditionally, executive help-seeking, which is asking for direct answers rather than guidance, has been viewed as a maladaptive learning behavior. However, this study suggests that when embedded in authentic tasks, this same behavior with AI can become a productive scaffold. Drawing on SRL, recent studies (Chang et al., 2023; Molenaar, 2022) support this reinterpretation by framing AI as a co-regulator that helps learners move from dependence to autonomy instead of passively accepting solutions. In other words, executive help becomes a gateway to metacognitive engagement. This study contributes to an emerging theoretical pivot, where executive help is not inherently adverse to learning if it enables deeper engagement, reflection, and reapplication (Cai et al., 2024; Msambwa et al., 2025). In other words, if AI is part of a thoughtful educational design, this can transform a potential shortcut into a genuine learning opportunity as the findings of this quai experiment indicate.

5.7 Pedagogical pivot: Role of instructor and course design

The integration of AI into university classrooms marks a pedagogical inflection point, not merely a technological shift (Jain et al., 2025; O'Dea, 2024). As AI can absorb lower-order cognitive tasks (Niloy et al., 2025) such code and content generation, the instructor can leave AI to support personalization, feedback, and content generation (Chang et al., 2023; Nguyen, 2025). Accordingly, the instructor role needs to evolve beyond lecturing toward mentoring, metacognitive modeling and epistemic coaching (Cai et al., 2024; Mollick & Mollick, 2024). Mentoring supports students in connecting ideas, reflecting on learning, and building their own understanding (Mollick & Mollick, 2024). Metacognitive modeling includes lively demonstrating thought processes and critical skills in action to help students direct their own learning (Mollick & Mollick, 2024). Epistemic coaching includes guiding students to question and evaluate the quality, sources, and limitations of knowledge (Cai et al., 2024). The importance of this shift is evident in student feedback, with students noting what they learned most when their instructor modeled how to critically and strategically navigate data curation with AI assistance. One student noted that this approach helped them not only read and understand AI-generated code but also catch and correct AI errors, while another emphasized that the mentoring and hands-on engagement in this course sparked genuine interest and readiness for real research. This pivot requires rethinking established frameworks. Nguyen (2025) calls for faculty development around ethical AI integration and metacognitive modeling, while (Jain et al., 2025) advocate rethinking Bloom's taxonomy to include "co-curation" and "ventriloquizing" AI output.

The goal is to design learning experiences that prepare learners to achieve AI fluency (Jose et al., 2025) instead of being passive operators. This can be achieved through curriculum strategies aligned with the zone of proximal development, where AI provides scaffolding for complex tasks while the instructor guides the crucial stages of synthesis and reasoning (Cai et al., 2025). For example, in the Environmental Data Science course (Elshall, 2025) the instructor deliberately guided students through the initial stage of developing research questions, the intermediate stage of data curation, and the final stages of synthesis. To ensure sustained engagement, the term-project was structured with mandatory checkpoints requiring instructor interaction, including a required project approval meeting before work could begin, a graded interim report to monitor progress and address challenges, regular office-hour meetings, and a final class presentation before the final report is due. This design guarantees that while students use AI for execution, their core research direction and analytical reasoning are developed and refined through direct mentorship. To achieve this model, where AI is a tutor and the instructor is a mentor while preserving student autonomy, course designs must be intentional and structured accordingly. Thus, guiding students through the challenge of building reliable knowledge from complex digital sources is no longer optional, but a pedagogical imperative in the AI era. Table 3 outlines key pedagogical strategies for this structural design. Together, these principles point to a shift from banning or uncritically adopting AI toward regulating AI. However, beyond key pedagogical strategies in Table 3, Carvalho et al. (2022) promote co-design of learning between educators and learners to reimagine education and build adaptive skills for an AI-driven future.

Table 3. Key pedagogical strategies for AI integration. Course materials, assignments, and sample exam questions that exemplify these strategies are available (Elshall, 2025).

Pedagogical Strategy	Implementation in Course Design
Course structure: Scaffolded AI integration	Introduce AI tools progressively where curriculum moves from no-AI tasks (non-AI checkpoints) for foundational knowledge, to structured AI use on intermediate assignments, culminating in open AI use on authentic, ill-structured projects
Assessment method: Hybrid assessment design	Blend AI-resistant tasks such in-class exams for foundational skills, multi-step case study with structured AI-use for critical thinking assessment, and AI-assisted authentic projects for applied skills assessment
Support mechanism: Mandated instructor checkpoints	Structure projects with required interactions, such as a mandatory proposal meeting, a graded interim report, regular progress meetings and a class presentation before final report due to ensure direct mentorship
Cultural foundation: Process transparency	Create a partnership and trust with students by transparently communicating the pedagogical rationale for the course AI policy, explaining why AI is restricted for foundational tasks and how to leverage it effectively in later, authentic work
Instructor role: Metacognitive modeling	Instructor "thinks aloud" to demonstrate how to critically evaluate AI outputs, data curation with AI assistance, and troubleshoot code
Target skill: Metacognitive reflection	Embed explicit prompts within assignments that require students to reflect on why and how they use AI, to encourage self-regulation and strategic thinking over simple recording
Student monitoring: Early warning system*	Create an early warning system for overreliance or disengagement by for example implementing brief, regular AI reflection logs for students to record their AI use, confidence levels, and points of confusion

*Not implemented in this course

5.8 Generalization and transferability

While this study centers on a specific environmental data science course, its findings offer broader implications for scalability and transferability across disciplines and contexts. The observed benefits, which are enhanced performance on authentic tasks, increased learner agency, and no erosion in conceptual mastery, reflect structural principles that are not discipline-bound but depends on alignments between learner regulatory needs, task nature, and learning goals. Thus, the study design principles are transferable across disciplines with tasks that are ill-structured, data-rich, and require open-ended inquiry. These are settings where learning gains from AI are most pronounced (Cai et al., 2024). This suggests strong transferability to other domains with similar task profiles such as engineering design. Moreover, the hybrid assessment model of FACT is not domain specific (Elshall & Badir, 2025). Awadallah Alkouk & Khlaif (2024) argue that hybrid assessment designs as key for preserving conceptual rigor while using AI as a collaborator in applied performance. Awadallah Alkouk & Khlaif (2024) findings validate the feasibility of AI-resistant checkpoints and process-based evaluation across varied educational environments (Table 3).

However, successful generalization hinges on faculty readiness and institutional scaffolding. As Fu & Weng (2024) emphasize, without instructor training and curriculum innovation, AI risks being either underutilized or misapplied. Models like the human-centered AI (Fu & Weng, 2024; Renz & Vladova, 2021) and AI literacy frameworks (Kong et al., 2024; B. Wang et al., 2023) offer pathways for the professional development of educators in diverse settings. Transferability also depends on contextual adaptation. Cheah et al. (2025) warn that without localized policy guidance and instructional modeling such as meta-cogitative modeling (Table 3), AI integration risks becoming haphazard. Thus, generalization must be theory-informed but practice-tuned given institutional constraints, disciplinary norms, and learner profiles (Corbin et al., 2025).

Finally, this study contributes to the emerging paradigm shift (O'Dea, 2024) where AI is not simply a support tool but a cognitive partner demanding a rethinking of student roles, instructor identity, and curriculum design (Carvalho et al., 2022; Jain et al., 2025; Jose et al., 2025). As a cognitive partner, AI functions both as a co-regulator (Molenaar, 2022) and co-creator(Yuwono et al., 2024). As higher education enters the AI era, the AI-affordance alignment framework provides a transferable framework to guide responsible and scalable implementation of AI in diverse learning settings. AI, when used intentionally and aligned with learning goals, can support not only more learning, but better learning. In other words, AI integration does not replace the learner but reshapes the task to be more authentic and represents the instructor as a mentor. This alignment does not undermine but serves academic integrity and cognitive growth.

6. Study limitations

While quasi-experimental study offers promising support for the AI-affordance alignment framework, several limitations constrain generalization and causal inference.

6.1 Small sample size and single-site design

The small sample size (n = 25) limits statistical power, while the single-course, single-institution design limits external validity. With a small sample size, contextual factors (even with strong controlled conditions across cohorts) may have shaped outcomes. While effect sizes for authentic tasks and foundational knowledge performance were large, behavioral and affective trends such as shifts in help-seeking and AI reliance should be interpreted cautiously. Thus, reported behavioral and affective trends are suggestive, and broader replication across courses and institutions is needed to confirm these patterns.

6.2 Causal inference cautions

Although the AI upgrade was the key intervention, we cannot fully isolate its effects from other cohort-level variables, such as motivation, engagement, or prior exposure. Equivalence in early scores and experience suggests a fair comparison, but unmeasured influences (e.g., informal peer support) may have contributed to gains. Thus, casual inferences should thus be viewed as suggestive, not definitive.

6.3 Data modalities

Though this study used surveys, performance data, and reflections, behavioral insights relied heavily on self-report. Future work should incorporate system logs, prompt histories, and fine-grained interaction data to better capture real-time help-seeking behaviors and distinguish effective engagement from passive outsourcing.

6.4 Critical thinking and long-term cognitive impacts

A key limitation of this study is its focus on performance outcomes and foundational erosion without directly measuring the quality of underlying cognitive processes including critical thinking. Additionally, we did not directly evaluate whether the observed performance gains were accompanied by deeper cognitive engagement, or conversely potential long-term skill or cognitive erosion. The cognitive-debt hypothesis raised by Kosmyna et al. (2025) remains a critical and unexamined question in this authentic learning context. Integrating the detailed cognitive metrics from lab-based studies (e.g., Kosmyna et al., 2025) into scaffolded, semester-long designs like ours is a critical future work to understand if the AI affordance alignment can deliver authentic performance gains while preserving the deeper cognitive functions that sustain lifelong learning.

6.5 Study contributions and significance

Despite these limitations, this study provides strong quasi-experimental evidence that well-aligned AI integration can improve authentic performance without eroding foundational knowledge. Acknowledging the abovementioned constraints, the study serves as a valuable proof-of-concept for the AI-affordance alignment framework and establishes a foundation for future, larger-scale research. Given these constraints, the findings offer transferable insights into designing effective, human-centered AI pedagogy.

6.6 Technological volatility

The above study contributions and significance reflect the capabilities of AI tools at a specific point in time. As AI tools rapidly evolve, their cognitive affordances and associated learning impacts will shift. Jose et al. (2025) recommend that AI-pedagogy research adopt rolling or longitudinal designs to capture AI evolving impact. However, we argue that AI is not merely a technical shift, but a deeper epistemic transition as AI increasingly participates in regulation and generation of knowledge. Thus, higher education needs to evolve to remain relevant in an era defined by human-AI collaboration. Specifically, we propose that pedagogical design is a key constat that transforms AI advancements into learning opportunities.

7. Societal implications: Higher education in the AI era

7.1 Disruptive innovation

While knowledge creation was once dominated by humans, we are now seeing a shift towards human-AI co-creation (Jain et al., 2025; Lee et al., 2024; Lim et al., 2023; O'Dea, 2024; Wu & Chen, 2025). Consequently, the integration of AI in higher education necessitates a shift from traditional content delivery to managing co-agency between humans and machines (Gonsalves, 2024; Jain et al., 2025; Molenaar, 2022; Philbin, 2023). Other opportunities include AI as co-teacher (Niloy et al., 2025), human-AI co-creation of knowledge (Yuwono et al., 2024), and educator-learner co-design of AI-mediated learning (Carvalho et al., 2022). This is creating a new paradigm of human-AI collaboration where pedagogy needs to evolve, for example, to teach students how to question, verify, and ethically manage AI-generated content (Fu & Weng, 2024; Gonsalves, 2024; Nguyen, 2025). With each major technological advance, students need to acquire new competencies not only in technical proficiency, but also in higher-order skills such as critical thinking, delegation, evaluation, and epistemic responsibility (Gonsalves, 2024; Melisa et al., 2025; Xia et al., 2024). Table 4 illustrates this pedagogical evolution, showing how pedagogical design can adapt across increasing levels of human-AI collaboration.

Table 4. Advancement of AI capabilities and required pedagogical shifts

AI Affordances	Description	Example	Pedagogical Design
Pre-generative AI (Baseline)	Tools for calculation or information retrieval with human performing all synthesis and analysis	Using Google Search to find EPA datasets or using statistical software to run a pre-programmed regression analysis	Core competencies: Foundational information literacy, manual research skills, data interpretation, and proficiency with specific software
Foundational AI (c. 2022-2024)	AI as a conversational tool for brainstorming, summarizing text, and generating codes with human directing each step	Asking AI to write a Python code to plot pre-cleaned data or perform regression analysis	Builds on core competencies: Effective prompt engineering, critical evaluation of AI outputs, and understanding AI ethics
Multimodal AI and early agents (c. 2024-Present)	AI as an interactive workbench capable of analyzing data, interpreting images, and executing multi-step workflows with a single command	Uploading a raw CSV of water quality data and asking the AI to clean, analyze, and visualize the trends of nitrate levels over time	Expands to include*: Designing and validating multi-step analytical workflows, interpreting complex AI-generated analyses, and debugging complex AI processes
Autonomous scientific agents (hypothetical future)	AI acts as a research collaborator, capable of independently designing and executing complex projects, from hypothesis to conclusion	Providing a high-level directive: Investigate the impact of recent urbanization on local watershed and propose mitigation strategies	Additionally: Meta-competencies and even re-evaluation of human expertise in the AI era, which are critical areas for pedagogical research

* Not implemented in this course

7.2 Designing for human expertise

While current generation models (i.e., multimodal AI and early agents) fail as the complexity of the task increases (Shojaee et al., 2025) and the precise future of AI affordances is unclear, the hypothetical example of a future autonomous scientific agent in Table 4 serves as a thought experiment. As scientific agents continue to evolve (Ren et al., 2025), this endpoint in Table 4 or comparable examples (Tang et al., 2025) can shape long-term pedagogical strategies including development of meta-competencies and re-evaluation of human expertise in the AI era. These meta-competences include ethical grounding and goal alignment to ensure that as humans delegate tasks to AI, they maintain strategic and responsible oversight (Chaffer et al., 2025). This re-evaluation of human expertise includes shifting focus from routine tasks, which can be automated, to "durable competencies" that are uniquely human, such as creative problem-solving, strategic thinking, and ethical judgment (AI Alliance, 2024). In addition, the re-evaluation of human expertise is not merely an economic question but an existential one (Edelman, 2025; Kulveit et al., 2025). This opens a critical research domain focused on redefining the nature of uniquely human expertise and ethical grounding in a digital world with advanced automation (Elshall et al., 2022).

While this study focuses on pedagogical design, the broader impact of AI on higher education demands a strategic shift from reactive adaptation to proactive integration. As such AI is not a disruptive innovation to be managed, but to be intentionally integrated with forward-thinking designs that anticipate evolving AI affordances (Carvalho et al., 2022; O'Dea, 2024). This transition extends beyond pedagogy to require significant curriculum redesigns that address the evolving demands of an AI-driven society and labor market (Abbasi et al., 2025; Jaramillo & Chiappe, 2024; Liang et al., 2025). In addition, this transition is institutional, challenging the longevity of fixed syllabi in favor of adaptive as AI has the potential to open different learning pathways (Jose et al., 2025). On the other hand, this transition presents risks, including the potential for epistemic decline and cognitive atrophy as learners outsource critical judgment (Kosmyna et al., 2025; H.-P. (Hank) Lee et al., 2025), the propagation of inherent AI biases (Bender et al., 2021), unresolved questions of academic authenticity (Nguyen, 2025; N. Wang et al., 2024; Yusuf et al., 2024), and other risks reviewed by Sengar et al. (2024). Therefore, instructors and institutions can adopt a dual strategy by implementing immediate adaptations such as revised assessments and AI literacy, while proactively preparing for a future defined by dynamic human-AI collaboration. While this future is speculative, multimodal AI that was emerging (Sengar et al., 2024) is now an active reality. This requires anticipating how AI capabilities will evolve at different intervals and proactively planning pedagogical strategies and curriculum development in alignment with those trajectories (Jaramillo & Chiappe, 2024; Walter, 2024). Thus, instead of chasing a moving target, educational design should carefully examine AI future development to empower learners with transferable competencies that will endure in an AI-driven future.

8. Conclusions

This study examines how advances in AI affordances reshape learner approaches to learning, particularly their help-seeking strategies and engagement, and how these behavioral shifts translate into performance on tasks varying in authenticity. This study provides quasi-experimental evidence by comparing two cohorts in an identically delivered environmental data science course, thus isolating the impact of a single generative AI upgrade. Results provide evidence that when advanced generative AI tools are aligned with authentic learning tasks, significant performance gains can be achieved without eroding foundational knowledge. This is shown by authentic project scores rising from a mean of 68% to 87% ($p < .001$), while final exam scores remained stable. The performance gain on ill-structured projects without exam impact is accompanied by shifts in student learning behavior toward more autonomy and positive sentiment. By redistributing cognitive load, AI allowed students to experiment more freely, and accordingly help-seeking behaviors shifted from peer reliance toward more autonomous experimentation correlating with the empirical findings of Annamalai et al. (2025). In addition, positive sentiment toward AI support increased from 41% to 77%, despite the doubled acknowledgement of potential over-reliance. Thus, AI upgrade can shift learner behavior toward more autonomy leading to affective and authentic gains that can determine sustained engagement. However, given the study small sample size (n=25), single-site, and short-term, these behavioral and affective trends should be interpreted with caution and warrant broader replication and examination. In addition, this study did not investigate the impact of AI upgrades on student critical thinking and cognitive development.

Given these findings and limitations, our central proposition is that the convergence of improved performance, adaptive behavior and positive affect is not an automatic result of AI upgrade alone, rather AI upgrades improve learning when paired with effective pedagogical design. This highlights the importance of pedagogical design to cope with advances in AI tools. Specifically, aligning AI affordances with task authenticity, pedagogical goals, and learner self-regulatory learning needs is key for improving learning outcomes. This can be achieved through pedagogical strategies including scaffolding AI use, blending assessment methods, mandating instructor checkpoints, active instructor mentoring, and promoting metacognitive modeling and reflection as implemented in this study. Thus, advances in AI can continue to improve learning provided that effective pedological design is in place. In other words, the intentional alignment of AI with pedagogical purpose is a critical mechanism for improving learning while safeguarding learner agency. Future research should test AI-affordance alignment frameworks in larger, more diverse settings and explore both short and long-term positive and negative effects.

Finally, our empirical case study, which operationalizes this AI-affordance alignment framework, offers insights for future work on pedagogical design in STEM education. Our findings show that when AI affordances are properly aligned, learners become more self-directed and excel on authentic tasks without impacting conventional assessments. This aligns with an emerging pedagogical pivot, especially for research-based courses with a focus on ill-structured problems. In other words, AI as a co-teacher (Niloy et al., 2025) can absorb lower-level procedural tasks, freeing instructors to mentor higher-order inquiry and creative synthesis. This continual redefinition of instructor and learner roles demands a forward-looking educational design that enables STEM learners not only to endure, but also to thrive in an AI-driven future.

Data availability statement

Data supporting this study are available at Elshall (2025)

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Competing interests

None

AI assistance statement

Coding for data analysis and plotting were performed using Python with assistance from GPT-4o. GPT-4o and Gemini 2.5 Pro were used to provided review comments, and to improve text clarity, succinctness, logical flow, and overall polish. AI contributions were verified for accuracy and relevance.

Ethical standards

The research meets the Institutional Review Board (IRB) of Florida Gulf Coast University.

Author contributions

Conceptualization: A.E., A.B., M.G. Methodology: A.E. Data curation: A.E. Data visualization: A.E. Writing original draft: A.E., A.B., M.G. All authors approved the final submitted draft.

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