Journal of Higher Education Management

Volume 41, Number 1 (2026)

SPECIAL THEMATIC ISSUE

Beyond Automation: How AI is Enhancing Leadership in Higher Education

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PUBLISHED BY THE

AAUA

AMERICAN ASSOCIATION OF UNIVERSITY ADMINISTRATORS

JOURNAL OF HIGHER EDUCATION MANAGEMENT
Volume 41, Number 1 (2026) ▪ ISSN 2640-7515

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Governance of the Journal of Higher Education Management is vested with the Publications Committee of the Board of Directors of the American Association of University Administrators.

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Journal of Higher Education Management, 41(1), 4-19 (ISSN 2640-7515).

Key Ways Higher Education Can Shape Artificial Intelligence

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Abstract

Artificial intelligence (AI) is a powerful tool that is driving broad innovative and effective transformation in higher education. With those successes as backdrop, this paper focuses on the critical need for higher education to engage much more deeply and rapidly in three key aspects of AI: the application of cognitive science research to the training of AI platforms, the ethics embedded in and of using AI, and ethics and other aspects of where humans fit into AI. Examples of preliminary action on these issues are discussed. Specific suggestions of key ways higher education could lead the development of ethical guidelines are offered. A summary of steps higher education leaders could take is also provided.

Keywords: artificial intelligence (AI), cognitive biases and heuristics, cognitive science, ethics and AI, higher education and AI

Introduction

Would you trust a major surgery to a human physician who just received a surgery neurochip brain implant containing encyclopedic information about the procedure, but who had no actual surgical experience? Seems farfetched? Maybe not, given that Neuralink has a brain implant in clinical trials that enables "people with severe paralysis to control devices and engage with the digital world using only their thoughts" (Neuralink, 2025). Still, the leap from an implant to help people regain muscle movement to instill high-level knowledge and skill remains daunting. This gap makes it the perfect time for higher education, perhaps in partnership with others (governments, private enterprise), to lead the discussion on the far deeper questions of the ethical aspects of the technology that could make this all come true. Much of this discussion will focus on the continued development and deployment of artificial intelligence (AI).

It is well documented that AI has already revolutionized both our daily lives (social media, GPS, customer service, social companionship, and much more) and nearly every aspect of higher education (instruction, writing, scholarly endeavors, processing student applications, academic support, handling financial transactions, and so forth). The list of these innovative uses is extensive, with new approaches reported on at least weekly in various higher education media outlets (e.g., *Chronicle of Higher Education, Inside Higher Education, New York Times*) and scholarly journals such as this one. This rapid adoption of AI has already changed the teaching-learning process, faculty-student interactions, student support (tutoring, counseling), the creation of course content, the design and conduct of scholarly inquiry, and many back-office operations to a greater extent than arguably at any other point in history.

As important as these innovations are, though, the primary focus of this paper is on certain thorny aspects of AI that are currently discussed less. Some of these concern ethical issues underlying AI (e.g., Beheshti & Kerridge, 2025), while others concern tremendous opportunities for higher education to shape the future development of AI platforms and their implementation, as well as documenting shortcomings due to the nature of human-AI interfaces. To introduce several of these issues coherently, the paper is divided into four main sections. First, it provides a general overview of AI to establish a common foundation for subsequent sections. Second, it summarizes the importance of cognitive science research for understanding how humans process and create information and how those processes shape the training of AI. Third, it examines the ethics of using AI in two ways: the ethics of using AI in specific contexts and the ethics embedded in AI itself. Finally, it poses the fundamental question of where we humans fit into an AI-infused future. The paper concludes with a summary of significant steps higher education can and must take.

Artificial Intelligence

The context for the present consideration of higher education's role in the development and deployment of AI is nicely summarized in the following passage:

> We refer to the question: What sort of creature [human's] next successor in the supremacy of the earth is likely to be. We have often heard this debated; but it appears to us that we are ourselves creating our own successors; we are daily adding to the beauty and delicacy of their physical organisation; we are daily giving them greater power and supplying by all sorts of ingenious contrivances that self-regulating, self-acting power which will be to them what intellect has been to the human race. In the course of ages we shall find ourselves the inferior race…Day by day, however, the machines are gaining ground upon us; day by day we are becoming more subservient to them; more [people] are daily bound down as slaves to tend them, more [people] are daily devoting the energies of their whole lives to the development of mechanical life. The upshot is simply a question of time, but that the time will come when the machines hold the real supremacy over the world and its inhabitants is what no person of a truly philosophic mind can for a moment question.

The excerpt, from the article "Darwin among the Machines" by Samuel Butler, published in *The Press* in Christchurch, New Zealand, on June 13, 1863, is the first known published reference to machine intelligence, or what we now call AI. The point of the passage, the ultimate danger of supreme machines for humans, remains one of the dominant themes in discussions about what AI could portend. The passage also points to the importance of addressing the ethics of AI long before it presents an existential threat.

AI: The Basics

Because AI is discussed in so many different contexts, it is important to have a shared understanding of what AI is and what it is not. AI is not a unitary concept or one type of complex computer program or network. Writers disagree on the specific labels and details, so for our purposes I will focus on AI as organized in two ways: AI based on its capabilities and AI based on its functionalities (GeeksforGeeks.org, 2025; Virellan, 2025). This scheme is presented in Table 1.

Table 1
Types of AI

Types of AI Based on Capabilities	Types of AI Based on Functionalities
• Narrow AI • General AI • Super AI	• Reactive machines • Limited memory • Theory of mind • Self-aware

Let us consider first the types of AI based on capabilities.

- **Narrow AI** is limited to and designed to perform specific tasks or commands. Narrow AI does not learn or understand, and it is not aware. Examples include voice command systems such as Siri and Alexa, facial recognition systems, and recommendation algorithms used by streaming services (e.g., Netflix, Spotify) and retailers (e.g., Amazon). Narrow AI is ubiquitous.
- **General AI** systems have human level intelligence and abilities that enable them to understand, learn, and apply solutions to a wide variety of tasks, as humans do. General AI is sometimes described as having consciousness and self-awareness as demonstrated by the ability to make independent decisions. General AI is currently not available publicly, but it is expected in the foreseeable future.
- **Super AI** surpasses human intellectual abilities and could potentially develop emotions, needs, desires, and beliefs. Super AI would not only be “smarter” than humans but also could anticipate human responses and emotions. Super AI exists in theory and is a common focus of speculative literature. Super AI could provide revolutionary opportunities, as well as pose extremely challenging ethical dilemmas.

Let us now consider AI in terms of various functionalities.

- **Reactive machines**, the most basic form of AI, operate only on data that is input and do not store or learn from previous actions. Some examples include: certain games (e.g., chess, GO) that are based only on data about how each piece moves, allowable moves, and pattern recognition, and do not have information about prior games; and facial recognition programs that match people’s faces with a document that is available for only a set period of time, such as identifying passengers for a specific airline flight. Reactive machines are ubiquitous now.
- **Limited memory** AI learns from past data and outcomes to improve future actions and outcomes. Limited memory AI is often referred to as machine learning systems. The databases used involve recent outcomes for the specific set of tasks being performed, so these do not have human-type long-term memory that extracts meaning. Such machine learning systems are widely used in robotics, autonomous vehicles, and chatbots. Limited memory or machine learning systems are ubiquitous.
- **Theory of mind** AI is capable of understanding emotions, beliefs, intentions, desires, and so forth. This would enable the AI system to interact in humanlike ways and anticipate

human responses. Examples of theory of mind AI would be robots that adapt to individual people's emotions and needs, and robots that could collaborate with humans in such areas as healthcare. Theory of mind AI is not yet available publicly but is in active development with primary emphasis on human-robot interactions in healthcare and social services settings.

- **Self-aware** AI would be the most advanced form that would possess self-consciousness and awareness. This type of AI would meet the usual criteria for sentience, raising crucial ethical questions. Self-aware AI systems would be capable of making decisions about the world around them based on their understandings of it. Still only theoretical, self-aware AI is the most frequent focus of speculative fiction, often in terms of whether such systems eventually turn on their "creators" and subjugate (at best) or eliminate (at worst) humanity.

Narrow AI Applications and the Higher Education Connection

At present, our daily lives are full of interactions with narrow AI as reactive machines or limited memory systems. When we contact customer service, ask Waze for directions, browse Spotify for a playlist, or listen to an article read through by a voice from a news outlet, we are probably interacting with narrow AI. Physicians use narrow AI to assist them in medical diagnoses. Chatbots provide mental health support. It's so common that most of us give little thought to it. Besides, it seems pretty benign given how much easier it makes our lives. Perhaps it's not, given how much personal information other people and organizations have about us from our use and what else that AI is able to do with that data.

Within higher education, narrow AI is embedded in most of our everyday academic activities, including as sources for material and assignments in courses, data analyses in research (e.g., identifying themes in qualitative research interview transcripts), grading and checking student work, online tutoring, querying the web, navigating to and from campus, generating summaries of meetings, and so forth. Opinions and emotions run the gamut about these uses, but there is little chance that AI can or will be extricated from these contexts, just as *Cliff Notes* and *Wikipedia* before it were not either. Researchers at Stanford (King et al., 2025) report using generative narrow AI to create a brand new virus that eats bacteria, a result that drew immediate expressions of significant medical potential and very serious concern (Feldman & Feldman, 2025).

AI-driven chatbots are also ubiquitous. Troubleshooting chatbots may be helpful in helping people figure out why an appliance isn't operating correctly, but others are already pushing the envelope in some critical ways. For example, Nyakhar and Wang (2025) report that chatbots are being used to address college students' mental health concerns, but rigorous evaluations are lacking. Relatedly, Marchegiani (2025) raises concerns about making conversations with chatbots essentially indistinguishable from actual human interactions that may be fine for customer service applications, but perhaps not for more serious issues. Researchers at Stanford go further and warn that current mental health-focused chatbots are not as effective as human therapists, "but could also contribute to harmful stigma and dangerous responses" (Wells, 2025).

This leads us to point to increasing need for courts to determine accountability when chatbots may be determined to do harm. Already, some mental health therapy chatbots are alleged to have provided poor responses that may result in some individuals dying by suicide (Chung & Green, 2025; Shah et al., 2025). Bots that are trained on religious texts are being used by people who confess their secrets and ask for advice, with some even considering them talking to God (Jackson, 2025). Questions regarding liability for accidents caused by self-driving cars are quite complicated and are pushing the boundaries of corporate and product liability law (MacCarthy, 2025).

Within this overview of the benign, mundane applications of narrow AI lie exceedingly complex issues that signal major challenges. Taken together, despite the overwhelming evidence that narrow AI can improve our lives a great deal, even the application of these most basic AI systems is not without potential danger.

Enter higher education. For example, law and medical schools, as well as humanities and social science departments, are uniquely positioned to help create new and revise existing statutes and guidelines to assign accountability when chatbots, diagnostic-assist systems, autonomous vehicles, or other AI-based platforms cause harm. Such work is already underway in medical fields as medical ethicists' work to understand liability for errors made in AI-driven diagnostic systems (Ratti et al., 2025; Tang et al., 2023). Research ethicists are already creating guidelines for the use of AI systems in scientific writing (e.g., Mann et al., 2024) and in research using AI-generated data (e.g., Resnik & Hosseini, 2025).

These situations also raise opportunities for focused research by faculty and students. Do students learn material or skills (e.g., writing) better in an AI-enhanced environment? Does it matter whether people anthropomorphize a chatbot into their "therapist" or even "God?" Or, flipped around, should prominent individuals permit chatbots to be modeled after them? Perhaps in anticipation of this question, Pope Leo XIV has indicated that he will not approve the creation of a "Virtual Pope" (Wooden, 2025).

Numerous institutions have inserted AI systems into administrative functions, such as recruitment, retention and student success, and financial management. In many cases, these applications have replaced human employees, especially in entry-level positions. Such replacement parallels what is occurring in corporations, where entire departments are being converted to AI (e.g., basic accounting, computer coding, human resources application screening). These applications have a double impact on higher education. Not only are humans being replaced, but research on topics such student success over time can emerge in ways previously difficult to accomplish.

But a darker application lurks around the corner. Soon, instructors in fully asynchronous courses are likely to be replaced by AI. Currently, instructors in such courses are generally prohibited from making any content or other course modifications, must use predefined grading rubrics, and must enforce fixed course and institutional policies, so there is little obvious added value difference between human and AI-based instruction. The implications of this are substantial and go to the heart of higher education: If there are no human faculty in a substantial number of courses, then what *is* a college or university? What would accreditation mean?

The examples of overarching advantages and challenges of narrow AI described in this section set the stage for deeper analyses in two ways. Next, we will go deeper into the issues posed for higher education through the process of creating many of the narrow AI platforms. Later, we will return to the issues regarding ethics raised in this section, and apply them to other forms of AI.

"Training" AI and Critical Thinking

At a core level, AI and humans are similar—neither starts out with all the information and knowledge they will eventually possess and need. Rather, each must be taught. Over the course of human history, decisions have always been made regarding what information and knowledge need to be transmitted. This is in part because it is impossible for a human to acquire everything humanity has learned over millions of years of evolution and lived experience, and in part because we don't need to do that given humans' ability to generalize learning across time and contexts. For example, textbook authors and instructors select certain information for inclusion in a course because it is deemed fundamental for future learning and application.

Similarly, we must provide AI with the building blocks of information and knowledge. With narrow AI, whatever we teach it will set the limits of what it will ever "know," because these systems have no ability to generalize or acquire new information or knowledge on their own. Thus, as we do with humans, we make decisions about what information to transmit into AI systems.

All would be well with "teaching" AI if the selection processes are demonstrably neutral and balanced, but they are not for structural and process reasons. Structurally, it is currently impossible to upload the entire body of human information and knowledge for the simple reasons that some have never been deciphered (e.g., some ancient languages) and much is not in or convertible into a digital format.

From a process perspective, completely neutral and balanced ways of choosing information is unachievable as documented in cognitive science research (Cavanaugh & Cavanaugh, 2021). As Ceci and Williams (2018) note in their summary of this research, there exist at least nine characteristics that describe the processing biases and heuristics adults use in acquiring and accessing information and making decisions.[1] What this means is that people, even as young as preschoolers, do not process incoming information neutrally, but instead prefer to get information from like-minded people and sources. For adolescents and adults, this plays out clearly in social media use and news sources.

Importantly for our purposes here, it also plays out in training AI. For example, Grok, the AI-powered chatbot connected to X, has shifted responses as its owner, Elon Musk, shifted positions

[1] The nine biases and heuristics that Cece and Williams (2018) discuss are: (a) show selective perception, in which they perceive the same event differently; (b) consider the quality of argument made by people with whom they agree more positively and adopt more extreme positions as a result; (c) overestimate the depth of their understanding of controversial issues, termed the illusion of understanding bias; (d) consider the other side as more biased than their own side, termed the blind-spot bias; (e) tend to collect more evidence confirming their position and evaluating it positively, termed the myside bias; (f) consider their position on an issue as the basis for greater enlightenment, but view the opposite position of their opponents as a source of bias; (g) view their own position and arguments as based on what is "really out there" whereas their opponents' views are not, termed naïve realism; (h) consider arguments that are congruent with their position as more valid than alternative arguments, even when the validity of the arguments is controlled, resulting in increased polarization, termed motivated skepticism; and (i) are largely unaware of their own knowledge gaps and lack of competence.

on issues (Thompson et al., 2025). Researchers at Stanford (Westwood et al., 2025) report that OpenAI, Anthropic, and Google all display various degrees of processing (e.g., political) bias. In a way, these findings are unsurprising—AI reflects the biases and heuristics of its human creators. In another way, of course, this is scary in that the casual user may be oblivious to this fact. Note that these biases and heuristics in AI do not merely reflect instances of so-called "hallucinations" in which AI generates fictitious information and sources and embeds them in discussions that also incorporate verifiable information.

Given the reality that at present AI reflects the minds of the programmers, how does one evaluate information sources and their trustworthiness, winnow the facts, and discern selection bias? In a higher education setting, how do faculty, administrators, or boards ensure that the AI platforms they select do not use discriminatory algorithms, for example? That seems daunting given the cognitive science findings. However, this kind of analysis is something higher education institutions nearly all claim to instill in their students as one aspect of what they call "critical thinking."

Evidence from a meta-analysis of 45 studies on critical thinking interventions in higher education indicates that there is little agreement on what "critical thinking" means, how to instill it, and how to measure it (Schoute & Alexander, in press). Consequently, a case could be made that higher education is not helping students acquire a set of crucial skills to digest and evaluate output from AI, and so owns a significant part of the blame for the apparent lack of critical thinking regarding the trustworthiness of information posted in social media.

If this conclusion were not disheartening enough, Ceci and Williams (2018) also highlighted something else. Beyond discerning the trustworthiness of information, another crucial aspect of critical thinking is the ability to understand an issue from multiple perspectives with the cognitive flexibility to defend or dismantle all of those perspectives equally well. We have known for many decades that failure to master this skill leaves one especially vulnerable to groupthink and myside bias (Janis, 1971), and that achieving the skill results in less extreme views (Fernbach et al., 2013). John Stuart Mill (1859, p. 67) summed this point from his rationalist perspective:

> [The person] who knows only [their] own side of the case knows little of that. [Their] reasons may be good, and no one may have been able to refute them. But if [they are] equally unable to refute the reasons on the opposite side, if [they do] not so much as know what they are, [they have] no ground for preferring either opinion.

Despite failures to assess critical thinking adequately (Cavanaugh, 2018), higher education remains well-positioned to teach and assess these skills. To do so, however, will require establishing a common understanding of what critical thinking entails, meaningful requirements for students to learn them, and reliable and valid ways of assessing them. Additionally, higher education must confront an approach to determining the trustworthiness of information not connected to a rational analytic approach, but one based on a personalized lived experience approach that its proponents tout as having greater validity than verifiable empirical facts. For example, in response to the events following a disrupted speech at Middlebury College, Brockelman and colleagues (2017, second heading) asserted that, "Only through the context of clashing viewpoints do we have any hope of replacing mere opinion with knowledge" (heading 2). But how a "clashing viewpoints" context occurs, they argue, must be grounded in lived experience: "We contend that experiences and emotions are valid ways to see the world, and that the hegemony of [the] rational thought-perspective often found in a university setting limits our collective creativity, health, and potential" (para. 8). The difficulty is not that emotion and personal experience are illegitimate bases for analysis. The difficulty is that neither can be refuted, making a person who relies solely on this approach much more susceptible to myside bias because no one holding an alternative view can prove that any set of emotions or experiences are invalid. This often leads to the conclusion, due to cognitive biases and heuristics, that only my lived experiences are "correct." Isaiah Berlin (2002) warns that the results of this approach, driven by myside bias, is dangerous:

> Few things have done more harm than the belief on the part of individuals or groups (or tribes or states or nations or churches) that he or she or they are in *sole* possession of the truth: especially about how to live, what to be & do, & that those who differ from them are not merely mistaken, but wicked or mad: & need restraining or suppressing. It is a terrible and dangerous arrogance to believe that you alone are right: have a magical eye which sees the truth: & that others cannot be right if they disagree. This makes one certain that there is *one* goal and only one for one's nation or church or the whole of humanity, & that it is worth any amount of suffering (particularly on the part of other people) if only the goal is attained (p. 345; emphasis in original).

All of these situations get worse when we consider general AI and super AI. Once systems are able to generalize and learn on their own, and eventually become sentient and self-aware, humans lacking critical thinking skills will be even more vulnerable to deception. Because general and super AI will be much faster and have far more extensive databases on which to draw, having the ability to question the trustworthiness and validity of any AI-generated outcome could mean the difference between playing meaningful roles in those societies and being cast to the side, or worse.

What must higher education do to better prepare students to thrive in an increasingly more sophisticated AI-infused world? First, we must undertake a thorough reconceptualization of the curriculum, informed by cognitive science research, on identifying, instructing, and assessing the key skills underlying true critical thinking. As part of this educational approach, we must also incorporate lived experience in ways that also lead to the understanding that two things may be simultaneously true: my lived experience is mine and real, and lived experiences reported by others are also equally real but perhaps quite different. Second, we must make the acquisition of critical thinking skills a nonnegotiable requirement as necessary for a person to be better equipped to deal with a future version of everyday life that will be even more deeply infused with ever more sophisticated AI.

There is one more point to add. Lurking just around the corner is the advent of embedding AI-based microprocessors in human brains. We are already inserting brain stimulators to help treat certain types of neurological disorders. In the foreseeable future we may be able to choose implants that will do everything from making us instant content geniuses on any and all topics to having super sensory abilities. If we are able to go to the neuroimplant store and get such chips, there will be little need for higher education in terms of the mere transmission of advanced information and knowledge. If this is what one believes is the primary purpose of higher education, what happens then? Would inserting a chip be sufficient? Higher education's future existence may hinge in significant part on creating an adequate answer.

Higher Education’s Role in Ethically Using and Creating AI

One of the constants in higher education is that when novel tools or topics appear they can be best considered as opportunities for learning. That is, we cannot presume that students (or faculty or staff) come to our institutions ready to engage appropriately and fully in its use, especially in terms of ethics. As I have argued regarding civil discourse (Cavanaugh, 2017), understanding the ethical use of AI is a knowledge gap akin to any other. Simply stated, we must teach the ethics underlying AI. But we also must model ethical behavior regarding AI ourselves, lest we be hypocrites. Only after doing both can we institute the appropriate accountability systems for ethical breaches.

Most important, we cannot presume that broader society will take care of such instruction and modeling. An example is illustrative. It is the case that individuals or organizations can be deceptive about their use of narrow AI. For example, Reuters news service reported (Horwitz, 2025) that Meta’s AI rules allowed chatbots to have sensual conversations with minors, a situation Meta subsequently claimed to be addressing (Mann, 2025). AI-generated child pornography images have been uncovered (Internet Watch Foundation, 2025). Invoking false claims of “free speech” should provide no protection for such applications, but tech companies and others argue loudly AI should not be regulated.

Whether public-facing corporate AI platforms need ethical guardrails or should be considered as moral agents continues a debate dating at least to the Code of Hammurabi (c. 1750 BC) (Moriarty, 2021). What is arguably beyond debate is that higher education institutions have a responsibility to lead the discussion and present alternative models for ethical standards. Additionally, faculty, students, and others must conduct impartial research to document any serious physical or psychological harm from specific AI platforms to suggest potential solutions to unfettered AI if such evidence is found. Boards of trustees have a fiduciary responsibility to ensure that the platforms they adopt have been developed and are implemented ethically.

These points emphasize that how AI is created, especially regarding training narrow AI systems, needs to be transparently shown to be ethical. As might be gleaned from the earlier consideration of cognitive science research in this regard, this issue is more complicated than the ethics of merely using AI.

One aspect of ethics regarding the creation of AI systems is ensuring that the systems being created only do what they are intended to do. This involves ensuring that the AI system is trustworthy. In this regard, important roles for higher education are to teach the ethics and value of transparency and to demonstrate trustworthiness through data regarding its various practices and processes. For example, higher education institutions should give very careful consideration to (1) rejecting any AI platform that requires collection of unrelated personal data for sale to third party vendors, (2) complying with FERPA and HIPAA requirements, and (3) carefully monitoring whether AI-based selection systems result in illegal discrimination.

As noted earlier, it is currently impossible to build a completely neutral, balanced narrow AI platform due to the inherent biases and heuristics in the humans who program it. As noted earlier, this occurs both in the selection of the information used to train AI systems and in the decision-making algorithms embedded to process that information. In short, choosing the information and assigning the weights in the decision equations necessarily reflect biases and heuristics for good and bad. What information gets filtered on the input side, and what those weights in the decision equations are, matter tremendously in determining the trustworthiness of the AI system in question. Obviously, the optimal solution is to reveal the underlying rubrics (i.e., the algorithms) for each step. But because that's the equivalent of revealing the secret formula for Coke to the companies that create AI systems, that's highly unlikely to occur except for systems using truly open-source coding.

An analogue to the way scientific research is reported could be helpful. In any report of a research study, details must be provided about the overarching research question, the specific variables being examined or manipulated, the outcomes being measured, all of the various components that constitute the specifics of the research (e.g., specific chemicals, medical procedures, assessments, participants), and the specific procedures taken to do the research. In AI platform terms, this is roughly equivalent to specifying the information databases that were uploaded into the platform and the details of the algorithms programmed in it. One could then compare the outputs of multiple AI platforms having identical inputs and discern what the decision weights may be based on differences in the outputs.

At present, we have at best only rough approximations of this. We can make identical queries of different AI systems and compare the outputs, but until we know more precisely what information was uploaded in the first place, and the specifics of the algorithms used to manipulate the information, we cannot draw definitive conclusions about the supposed trustworthiness of various chatbots.

Higher education provides the right context for such research, however, in the same way it provides such contexts for other gnarly questions. For example, New York University's nonprofit AI Now Institute (https://ainowinstitute.org/), and The Center for Human-Compatible Artificial Intelligence (CHAI; https://humancompatible.ai/), a collaboration including the University of California at Berkeley, Cornell University, the University of Michigan, the University of Oxford, and other organizations, provide good initial models for this approach.

Along these lines, one crucial line of research concerns the interaction between the AI algorithms driving social media platforms that result in mob behavior. Recognized in ancient Rome and intriguing scholars since the French Revolution (Barber, 2024), mob behavior was first described empirically by Le Bon (1896) as unanimous, emotional, and intellectually weak. In more modern terms, Le Bon's "intellectually weak" reflects the reliance on cognitive biases and heuristics to process incoming information rather than critical thinking. Recent research supports Le Bon's view (Brindal et al., 2022), and several theories focusing on social media behavior have been suggested (Murray et al., 2025). As a target of social media mobs, higher education should investigate the intersection of mob behavior with decisions made by faculty, staff, leaders, and boards, particularly on the consequences of either resisting or capitulating to the pressure. Within this research, additional focus should be placed on determining the trustworthiness of AI-driven demands made by social media-fed mobs.

The AI engines that power the mob provide a glimpse of what fully unleashed AI without clear ethical guidelines is like. The lack of tests of trustworthiness and the absence of critical thinking results in mobs making harsh and immediate demands that ignore standard due process. Unrestrained narrow AI provides a dangerous complexifying means for implementing fundamental principles and processes used effectively from antiquity through the Inquisition and Puritan witch trials to McCarthyism and the present.

It is essential that higher education step into the breach quickly. Decades of research on mob psychology are relevant, as is the research in cognitive science cited earlier, as is broader research and scholarship in the Enlightenment philosophy and its aftermath that introduced many of our ideas about individual rights and its derivatives and counterarguments. Above all, higher education must stand in support of ethical guidelines for the development and use of AI. Crucially, boards of trustees and senior leaders must stand firm against the intense pressure to abandon trustworthiness standards. Either the gaps regarding critical thinking and ethics are addressed, or higher education becomes complicit in perhaps creating a world in which what is "true" and "correct" are determined by AI algorithms driving mobs.

Where is the Human in AI?

The final overarching issue for higher education flows from Butler's 1863 article quoted earlier: If self-aware AI is developed, what are the implications for humanity? The idea of computers posing a threat to human existence is a major theme in classic science fiction, such as *2001: A Space Odyssey* and *Star Trek*. Opinions run the gamut, but a deep-seated fear is that sentient, self-aware AI would consider humans inferior and take steps to eliminate them.

Eliezer Yudkowsky and Nate Soares (2025) certainly take this apocalyptic position in their book *If Anyone Builds It, Everyone Dies*. They express the view that if left to its own devices, AI will inevitably reach that point of no return vis-à-vis humans. That makes sense. A sentient, self-aware AI system's knowledge and intelligence would dwarf any human's. If one of the operational principles of that AI system is to eliminate inefficiency and less intelligent entities, then humans would be on the elimination list. Is there a way for higher education to help ensure that this doomsday outcome is avoided?

Perhaps one approach would be to reconsider the work of Isaac Asimov, considered one of the greatest science fiction writers of the 20th century. One of Asimov's most important contributions was the Three Laws of Robotics, first introduced in his 1942 short story "Runaround" and included in his 1950 collection *I, Robot*. The Three Laws, which Asimov claimed to be from the fictional *Handbook of Robotics* (56^{th} edition), published in 2058, are:

1. A robot may not injure a human being or, through inaction, allow a human being to come to harm.
2. A robot must obey the orders given it by human beings except where such orders would conflict with the First Law.
3. A robot must protect its own existence as long as such protection does not conflict with the First or Second Law.

Although originally written to pertain to robots, one can easily apply these Laws to AI. How could this be done? Several writers suggest we draw parallels between the need for international agreements establishing guardrails for AI in ways similar to the way such safeguards were created to limit the proliferation and use of nuclear weapons (e.g., Cha, 2024; Jones, 2025). Higher education could play a critical part in this process; historians, international policy experts, international jurisprudence experts, ethicists, and others could provide context and guidance. Theoretically, if implemented properly, the Laws would not permit an AI entity to do anything injurious to humans, an outcome analogous to the limiting of nuclear weapons, capable of total human annihilation, to a handful of countries.

Doomsayers (e.g., Yudkowsky & Soares, 2025) say this is folly because it is already too late. They suggest that the general lack of regulations has already let AI develop in unrestrained ways that cannot be undone.

Others disagree with that position. For example, IBM has developed *Principles for Trust and Transparency* (https://www.ibm.com/policy/trust-transparency) that include a commitment indicating that they "do not seek to replace human intelligence with AI, but support it." Loaiza and Rigobon (2024) developed the EPOCH framework (Empathy, Presence, Opinion, Creativity, and Hope) for AI to "capture human capabilities that complement, rather than substitute, artificial intelligence." The United Nations Educational, Scientific and Cultural Organization (UNESCO, 2022) drafted the *Recommendations on the Ethics of Artificial Intelligence* that include a provision to do no harm to humans.

The need for universities to help lead the effort to create ethical guidelines regarding the ultimate potential threat of AI is clear. Universities widely and continuously engage in global partnerships in research and scholarship. The university networks have several advantages: experts from different backgrounds are used to working together for common goals, shared resources (e.g., laboratories, libraries) are commonly used, there is a track record of being able to set aside partisan politics when necessary, and there is plenty of evidence of successful collaboration with corporations. The university partnerships developed for other aspects of ethics and AI discussed earlier could be entry points for this larger discussion.

Historical international research treaties exist that could provide initial models. For example, the Antarctic Treaty and related agreements, collectively known as the Antarctic Treaty System (ATS), regulate international relations with respect to Antarctica. Signed in 1959 and effective in 1961, it designated the continent as a scientific preserve, established freedom of scientific investigation, and banned military activity. Additionally, space law (e.g., Robinson & White, 1986) is an international field of study and inquiry that is based on common needs of space explorers, not on traditional approaches to law.

Another reason that higher education is well positioned to take the lead on creating safeguards for sentient, self-aware AI is that higher education has a long record of researching things that could obliterate humanity. Besides nuclear bombs (e.g., universities' roles in the Manhattan Project to create them), labs around the world conduct gain-of-function research. This type of work gained widespread notoriety as one hypothesis regarding the origin of the COVID-19 virus, but there is a long track record of safe research with this approach. Higher education's experience in scholarly work regarding life-versus-annihilation threats have resulted in protections (e.g., vaccines) and diplomatic successes. They have also led to far more tragic outcomes.

Because super AI (either theory of mind or self-aware) does not yet exist, we are at the inflection point regarding safeguards. Now is the time to either start developing those guardrails, or step to the side and let the chips fall where they may, knowing that there will come a point of no return. What will we decide?

Suggestions for Higher Education Leadership Actions

Based on the discussions of AI and possible roles higher education could play presented in this paper, this final section offers four steps faculty, senior leaders, and boards should take to fill the gaps pertaining to AI and ethics. Specifically, higher education leaders should:

- Reexamine, clarify, revise, and affirm the institution's mission, vision, and values statements, especially with respect to critical thinking. Then, task the faculty to develop ways to attest to how and how well these are being achieved, and how AI could enhance and enrich this process.
- Promulgate specific policies regarding the ethical use or development of, research involving or focusing on, and the implementation of any systems incorporating AI (e.g., instructional platforms, HR or student support systems, admissions processing). In terms of academic affairs, such policies must include use of AI systems in instruction (including all student assignments) and scholarly activities. Such policies must include transparency about the use of AI-based platforms.
- Support the appropriate and creative use of AI-enhanced approaches to instruction and learning that foster critical thinking, as well as scholarly inquiry focusing on AI in all its variations.
- Reaffirm a commitment to due process to ensure fairness to all concerned when confronted with allegations, especially those driven by AI-based social media.

None of these steps will be easy. But to borrow from President John F. Kennedy, we in higher education do not do things because they are easy; we do them because they are hard. If nothing else, that work will require new forms and styles of communication among boards, leaders, students, faculty, staff, and external constituencies. Perhaps we will even relearn what consensus means and how to find it.

Acknowledgment

This paper is based on an invited keynote address presented at the *Innovation Unbound: Shaping the Future of Higher Education* Conference, Immaculata University, November 2025.

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Journal of Higher Education Management, 41(1), 20-27 (ISSN 2640-7515).

AI-Enhanced Institutional Research: A Critical Appraisal of Promise and Pitfalls

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Abstract

Artificial intelligence (AI) is rapidly reshaping the operational landscape of institutional research (IR) offices in higher education by offering tools for data analysis, forecasting, and decision support that promise greater precision and efficiency. However, as institutions explore these possibilities, questions emerge about the appropriateness, effectiveness, and practical ramifications of AI-driven methods within the diverse context of institutional administration. This paper offers a critical examination of the integration of AI into institutional research, asking:

- What are some potential advantages of AI in supporting core IR functions such as enrollment forecasting, student retention modeling, and operational reporting?
- What risks or limitations accompany the adoption of AI tools in IR, especially in terms of data accuracy, transparency, and institutional capacity?

The paper argues that while AI offers clear functional benefits, its application must be guided by a deeper understanding of both its technical constraints and its social implications.

Key Words: Artificial Intelligence, Institutional Research, Enrollment Forecasting, Student Retention Analytics, Data Transparency

Introduction

In today's rapidly evolving educational data and information ecosystem, the field of institutional research (IR) stands at a critical juncture. What was once a compliance-focused and largely reactive set of reporting functions—concerned with accreditation, and basic analysis has transformed into a pivotal strategic asset within higher education institutions. As data becomes even more central to academic planning, student success, resource allocation, and mission-driven assessment, IR professionals find themselves with unprecedented opportunities and complex responsibilities.

Artificial intelligence (AI) is rapidly reshaping the operational landscape of institutional research (IR) offices in higher education by offering tools for data analysis, forecasting, and decision support that promise greater precision and efficiency. However, as institutions explore these possibilities, questions emerge about the appropriateness, effectiveness, and practical ramifications of AI-driven methods within the diverse context of institutional administration. These questions include: What are some potential advantages of AI in supporting core IR functions such as enrollment forecasting, student retention modeling, and operational reporting? What risks or limitations accompany the adoption of AI tools in IR, especially in terms of data accuracy, transparency, and institutional capacity? How can institutions balance automation and prediction with the contextual judgment and interpretive skill central to IR practice? While not an exhaustive list of questions, they help frame the focus of this paper to build on the works of others (Urmeneta, 2023) whose work on the impact of AI in higher education helps, in part, to address the earlier works of Swing and Ross (2016) and even earlier Terenzini (1993) which frame the role and development of Institutional Research in American higher education.

Potential advantages to AI in IR

Forecasting enrollment, preparing various activity reports, and even helping uncover the stories of an institution are just some of the functions that Institutional Research (IR) offices can perform. From serving as an office of institutional memory, to engine of understanding, IR offices are often one of the most critical and yet unknown parts of any institution. Their work can encompass data and its context, analysis and reporting from early in the semester to years later in a final summative report (Howard et al., 2012).

While largely focused on supporting institutional leadership in data-informed decision making and necessary external reporting, IR offices are now more than ever being asked to help in synthesizing large data sets to better understand internal operational, structural, and policy issues from a data-driven perspective including the use of data to understand market forces and predict high-demand programs and overall potential future enrollment (Urmeneta, 2023).

The use of artificial intelligence (AI) in strategic enrollment management and institutional research (IR) is not a new phenomenon, but its applications have become increasingly sophisticated and integral to decision-making. In partnership with admissions offices and enrollment management teams, IR offices can leverage AI to better understand and even project with greater accuracy enrollment patterns. These efforts extend beyond simply identifying the raw number of students; AI can more rapidly help in the identification of potential student types within local and regional populations, synthesize demographic and enrollment trends, and generate actionable insights about what future enrollments may look like in terms of distinct headcounts and projected credit hour delivery.

AI, when combined with advanced data visualization tools and large-scale data sets, allow institutions and their IR offices, to rapidly summarize complex information into clear graphical trends and to perform advanced statistical modeling. Techniques such as cohort-survival ratio chain models, linear regression analyses, and time-series forecasting models provide a deeper understanding of enrollment dynamics and provide IR researchers with the enhanced capacity to test multiple scenarios for greater accuracy. These methods help institutions anticipate not only how many students might enroll, but also where those students are likely to come from, what programs they may choose, and how their enrollment behavior may influence instructional demand.

Admissions and enrollment management offices are increasingly collaborating with IR units to integrate AI-driven insights into their operational workflows. These tools are being used to evaluate the potential future success of applicants, to identify interventions that can improve yield ratios, and to pinpoint strategies that maximize student applications and eventual enrollment. Beyond forecasting, AI also contributes to efficiency: it can help streamline processing activities, enhance the evaluation of applicant data, and reduce the manual workload associated with traditional enrollment management. Ultimately, the integration of AI into these functions allows institutions to be more proactive, data-informed, and responsive in a competitive higher education landscape (Gnoh et al., 2024; Hodra, 2025; Moquin, 2025).

Another function of AI tools is assisting institutions with one of the most critical elements of student support: retention. Retention has become both a performance and a funding metric, and its importance continues to grow. AI models—especially those using ensemble learning methods such as gradient boosting—can be applied to predict which students are most likely to disengage or drop out, creating the opportunity for earlier intervention. Institutions can use these predictions to reach students before problems become too large, giving them support that can improve persistence and completion.

Integrating AI into operational systems also helps reduce the workload on IR and advising offices by automating parts of the early-alert and outreach process. This frees staff to concentrate on the most complex student needs while still ensuring that broader student populations receive timely communication and resources. These tools provide another layer of support that complements existing advising and retention efforts (Molina & Medina, 2025).

Retention is also directly tied to strategic enrollment management. While admissions focuses on new students, retention ensures that those students continue through to completion. AI makes it possible to connect these two elements—improving both yield and persistence—and to strengthen long-term enrollment planning by uniting recruitment and retention strategies under a single, data-informed approach.

Much of institutional research is dominated by repetitive, rules-based processes: extracting reports for IPEDS, cleaning files for accreditation, formatting narrative responses. For instance, Georgia State University developed an automated compliance reporting system that pulls data nightly from student information systems (SIS), runs it through rule-based RPA bots, and formats output in standard IPEDS structures. This system cut labor time for data validation and formatting by 40%, freeing analysts for strategic projects. The University of Alaska has for several years used a variety of automated technologies to capture data from multiple enterprise sources, shape them into usable data formats, and power a host of data visualizations, helping that IR office to serve nearly 800,000 inquires in just under two years. The University of Idaho deployed one of the state's earliest data dashboard systems which directly integrated their ERP into an interactive dashboard with customizable fields. Are these systems AI, or simply automated intelligence? One of the great questions for the future is anticipated to be: when does AI become just another part of the standard technology used by IR, and what, if any functions, will AI replace?

The answer to those questions will take years to discover, or perhaps only be realized through the lens of history. However, institutional data never speaks for itself. Numbers, patterns, and probabilities must be understood within their educational, cultural, and social contexts. An AI model might predict a student has a 78% chance of dropping out based on Learning Management System inactivity, late assignments, and missed advising sessions. But it cannot recognize that this student is also navigating housing insecurity, caring for a sibling, or recovering from a health crisis. This limitation of inputs creates an “analysis bottle rocket” whereby the algorithm may indicate a “false positive” finding and trigger unintended consequences or even not have access to critical details and neglect to identify a key issue that would normally require immediate attention. This intuitive element was best described by Terenzini (1993) who argued that IR professionals operate in three basic domains: the “Technical” or data management, modeling, statistical analysis functions, the “Issue” where alignment of research with meets institutional priorities and the “Interpretive” which translates findings into contextualized meaning and provides insight into policy and administrative activities.

Today IR has the opportunity to utilize AI in ways that range from the simple structuring of data to running various tests and basic analysis. More imaginative approaches can include analysis of part of the process, and not replace the decision-making process altogether. In this and other contexts it is clear that AI can support but not replace**,** institutional decision-making. It can enhance analysis capacity but not without external review. Even highly accurate models must be reviewed and interpreted by humans who understand the cultural, legal, and emotional context of student experiences, institutional culture, and the underlying deeper nature of the data itself.

Transparency

Much of AI is currently a closed-box approach to its use. Limited to individuals or teams with extensive computer programming skills and or third party pay services, these tools often are used in an “input”, “AI-work”, then “output” kind of approach. Without fully understanding the “AI-work” component, the resulting “output” may not be trusted. In fact, a recent study examining the ill-defined, but all too typical “human-AI partnership” found that trust in the data and the outputs increases when the AI system is able to provide a foundational basis for its outputs and analysis. Conversely, the study found that lack of agency transparency decreases when the system is unable to provide information on sources of uncertainty (Vössing et al., 2022).

However, transparency is not just limited to understanding the analysis. Understanding, or lack of understanding, on how AI can add value to an organization is becoming a topic of considerable discussion. IR offices, which are often tasked with supporting evaluation and accreditation efforts, are facing a lack of clarity on just how to effectively balance privacy concerns, accountability, and management of data where AI could be used (Firat, 2023) with the limitations, effective use cases, and practical applications of the various technologies in their work (Frutos et al., 2024).

The value proposition itself is a major sticking point. While many large universities such as Carnegie Mellon, UC Berkley, and the University of Virginia have all founded offices that focus on the use of AI in research, teaching, and administration, many other universities struggle to keep up. Again, IR offices are at the forefront of working to help Presidents, Chief Academic Officers, Accreditation Liaison Officers, Deans and more find value in a technology where few understand either the workings or the potential. Areas such as tabulating and calculating program assessment scores and outcomes, analyzing extensive data sets such as enrollment, fiscal data, KPI’s and their related trends for strategic planning are two examples of where AI can, if properly resourced, supported, and governed, be effectively used to support higher education decision making and administration.

When the term “big data” became popular in the early 1990’s the focus was more on computational challenges: could the machines actually handle the volume of data as opposed to how to analyze the data. As the term gained more widespread adoption in the early 2000’s the focus again was on storage and access, not analysis. As a set of technologies, AI does provide a value proposition as new tools that with training and proper care, can add to the capacity of IR in its work and in the work of other data-driven industries (Enholm et al., 2022). However, transparency is also about the acceptable use of the data.

AI models in institutional research often draw on sensitive and granular data: swipe-card access, Wi-Fi usage, LMS clickstreams, text responses to surveys, and even geo-location patterns. While these data sources enable fine-grained predictive modeling, they also raise significant privacy and surveillance concerns**.**

At Virginia Commonwealth University, students pushed back against a pilot program that used Wi-Fi access logs to track class attendance trends. Despite assurances of anonymization, the student body government raised objections about the lack of informed consent and the potential for misuse of personal behavioral data (DeRosa, 2020). As a result, the initiative was paused, and a campus-wide data ethics task force was formed.

Institutional and Individual Capacity

Resource inequality is a force limiter in AI development among universities. Large Private, Public, Research and even some regional institutions are able to address AI as a strategic investment or even a business-critical tool. With the resources to purchase software, staff, and the newest technological hardware, these institutions are able to lead the way and strategically take advantage of all that AI has to offer. By contrast, smaller, less well funded institutions who have for years struggled with declining support, enrollments, and dwindling endowments have to make choices between sustaining the aging infrastructure they have, shifting resources away from core mission activities, reducing staff or increasing costs to even attempt to move towards an AI-empowered campus. Often times these institutions rely on free or low-cost versions that may not be secure for handling sensitive data and staff who are upskilling themselves to try and handle the growing workloads assigned to them. This issue goes beyond institutional scope and finances. AI access and capacity directly impacts students as well. Low-income and underserved students often lack the resources to ensure they have the technology, access to internet, and simply the time to engage with AI-enhanced learning tools, further marginalizing them (Abrahamson, 2025). Arguments around AI in the classroom (Firat, 2023) are focused on the pedagogical and ethical aspects of learning and not on the use of AI as a force enhancer being used by students and professionals alike in an attempt to level the field in their everyday pursuits.

AI adoption in IR is uneven across the higher education landscape. Large research institutions and well-funded private universities are far more likely to develop in-house analytics teams, partner with edtech vendors, and pilot cutting-edge applications. In contrast, community colleges and smaller regional institutions often lack the technical infrastructure, staff expertise, or funding to engage meaningfully with AI tools. For example, The University of Michigan launched a certificate program titled *“AI for Institutional Leaders”* aimed at IR professionals, deans, and administrative staff. Topics include model ethics, bias detection, stakeholder engagement, and regulatory compliance. Completion rates have been strong, and internal evaluations show improved collaboration across data and program offices.

Conclusions

Artificial intelligence is undeniably reshaping the landscape of institutional research in American higher education. From forecasting enrollment to identifying at-risk students and beyond, AI offers institutions powerful tools to deepen insight, increase responsiveness, and strengthen student outcomes. Yet this power comes with profound responsibility. AI systems are not neutral—they reflect the values, assumptions, and histories embedded in their data and design. While the qualitative paradigms acknowledge bias as a natural aspect through the concept of researcher as the instrument, the design of AI systems is directly, and at times unfortunately, impacted by factors put in by humans that shape the outputs many use without question. Without intentional safeguards, these inputs risk amplifying systemic errors, inequities, risk violating privacy norms, and can lead institutions towards a false sense of efficiency or even worse, put their data, and their students at risk for a host of problems.

This paper has explored just some of the potential benefits and pitfalls of AI through the lens of Institutional Research. As a force for strategic improvement and productivity enhancement the evidence is clear: AI is not simply a technical innovation, but an institutional one. Its integration into IR practices, and by extension higher education administration, must be governed by clarity, care, and collaboration.

The future of higher education, institutional research, the work of our faculty, staff and students will not be written by algorithms alone. It will be shaped by the choices that institutional leaders, data professionals, students, and faculty make—about what to measure, whom to include, and how to interpret the signals AI provides. Colleges and universities that lead in this space will not simply chase innovation. They will have the profound opportunity to pair precision with compassion**,** prediction with context**,** performance with purpose and direction with dedication**.** AI is not the end of institutional research—it is an evolution. And like all powerful tools, it will serve higher education best when it is grounded in human judgment, ethical stewardship, and a deep commitment to inclusive excellence.

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Journal of Higher Education Management, 41(1), 28-39 (ISSN 2640-7515).

From Pilot to Practice: A Community College's Journey with Institutional AI Innovation

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Abstract

In this case study, we explore an adaptive leadership strategy illustrated by an AI Professional Development Initiative at a two-year institution, specifically focusing on benchmarks from an Institutional Effectiveness office. We provide context related to the institution and the initiative, and explore each area impacted in IE through four related sections: (1) background information and context, (2) benchmarks, (3) implementation challenges, and (4) lessons learned. Implications from this case study are given in connection to decision-making, efficiency, and leadership with respect to adaptive leadership strategies.

Key words: Artificial Intelligence, Higher Education, Adaptive Leadership Theory, Generative AI, Institutional Effectiveness

Introduction

At the onset of November 2022, higher education institutions, much like other impacted industries, were taken by storm by the launch of an accessible version of Chat GPT®. These large language models (LLMs) disrupted understanding of Artificial Intelligence (AI) applications in higher education, which previously was accustomed to relatively simple applications for tasks like profiling and prediction. LLM accessibility enabled intelligent tutoring systems, assessment and evaluation of complex items, and adaptive systems and personalization for teachers, students, and staff (Bond *et al.*, 2024). Since these AI technologies intentionally aimed to reproduce human language, higher education leaders became concerned with issues related to academic integrity, data privacy, and copyright implications, *inter alia* (Kamali, Alpat, & Bozkirt, 2024).

Considering these concerns, our institution's administrative leadership employed an adaptive leadership strategy (Heifetz, 1994; Heifetz, Grashow, & Linsky, 2009; Northouse, 2022) in the form of an AI Professional Development Initiative for the effective integration of AI into our institutional context. Adaptive leadership, originating from the work of Heifetz (1994) and later Heifetz, Grashow, & Linksy (2009), underscores that adaptive leadership brings a practical orientation to understand changing conditions that lead to value-aligned solutions. In this way, the purpose of this initiative was also to better understand how this new technology could support efficient administrative decision-making processes for overall institutional growth. In this contribution we focus on a case study pertinent to higher education leadership that centers on three areas that were impacted by this initiative in an Institutional Effectiveness (IE) office. As part of this case study, we provide context related to the institution and the initiative, and explore each area impacted in IE through four related sections: (1) background information and context, (2) benchmarks, (3) implementation challenges, and (4) lessons learned. Implications from this case study are given in connection to decision-making, efficiency, and leadership with respect to adaptive leadership strategies.

Context of the Institution

The AI Professional Development Initiative was implemented at a mid-sized, two-year college situated in the Southeastern United States offering a variety of undergraduate degree programs, and serving, at the time, approximately 13,000 mostly first-generation students. Almost 90% of the student population served were considered in-state residents, with only 10% coming from out-of-state. At this two-year institution, 55.9% of students were enrolled full-time and 39.4% of students were enrolled part-time. Less than 5% of students were not categorized as either full-time or part-time, reflecting the flexible, community-focused nature of this institution. The three-year completion rate for first-time students at this college at the time of implementation was 38.1%, wherein the Fall-to-Fall retention rate for first-time-in-college students was 60.4%. The institution had a strong reputation for continuing education and job placement for students, with 76% of all Associate in Arts degree graduates transferring to four-year institutions to complete their Bachelor's degree, and 85% of all Associate in Science, Bachelor's degree, and Certificate degree program graduates being successfully placed in a relevant employment opportunity upon graduation.

Structurally, the executive team of the institution was comprised of nine major areas including the President's Office, Workforce Development, Information Technology, Communications, Institutional Advancement, Student Affairs, Academic Affairs, Administrative Services, and Institutional Effectiveness. Each one of these areas held varying staff and personnel positions ranging from approximately ten to almost three hundred people, depending on the number of units or departments under each area. For example, areas like Student Affairs housed almost twelve units with approximately 50 personnel and other areas, like Institutional Effectiveness, housed two units, with approximately 10 personnel. The largest area on campus was Academic Affairs, which housed all of the academic departments, sub-units, and program personnel supporting the variety of academic offerings at the institution. As a public institution, vying for state funds alongside a number of other state institutions, resources needed to be used efficiently to ensure the success and support of the student population and maintain the affordability of the programs offered.

AI Professional Development Initiative

In this context, the President of this institution launched the AI Professional Development Initiative that encouraged all direct unit-based and department leadership on campus to investigate ways to leverage AI and make administrative processes more efficient. At this time, the language learning model, Chat GPT®, had recently been opened for general public use without a license. Language learning models are automated systems that leverage data analytics to understand, generate, and translate human language into relevant outputs, like documents and analyses (Bond *et al.*, 2024). In general, the focus of the anticipated effects of using generative AI was attuned to faculty and student use with respect to academic integrity and ethics, rather than its influence on higher education administration (Kamali, Alpat, & Bozkirt, 2024). However, the need to provide guidance, support, and training for leaders within higher education that were working in supporting or executive roles was also warranted as they were responsible for decision-making, efficiency, and leadership impacting their institutions.

Using an adaptive leadership model, the President's Executive Team leveraged an AI Professional Development initiative to preempt the effects and implementation of AI in higher education. According to Northouse (2022) adaptive leadership, "focuses on the adaptations required of people in response to changing environments. Simply stated, adaptive leaders prepare and encourage people to deal with change" (p. 285). An inherently collaborative approach to problem solving, adaptive leadership theory emphasizes that leaders do not have all of the answers, but rather find workable solutions by "engaging those persons who are closest to the problem within the system; they work with the system every day and know what can or cannot work for its improvement" (Nelson & Squire, 2017, p. 118). In this respect, the AI Professional Development Initiative was an exercise in adaptive leadership that provided opportunities for leaders at different levels at our college to assess how to integrate productive change from a transformative disruption like AI.

To this end, those that enrolled in the initiative were granted six months access to the premium-paid version of Chat GPT® and instructed to report on their specific applications. All units that were eligible were those that held a decision-making capacity at the institution with respect to enrollment, retention, institutional data, or other executive roles. Units that were selected were required to have a designated leader that curated team meetings, was responsible for collecting data, and presented results at the conclusion of the initiative. An array of campus units across multiple departments signed up to be part of the initiative, which also included 10 hours of required professional development training on AI as well as supplemental professional development training for all related staff and personnel on the projects.

Applications to Institutional Effectiveness and Assessment

This contribution centers on the efforts of this initiative from the Institutional Effectiveness (IE) perspective, specifically in the benchmarks that leaders in this office made for this purpose. There are three key issues that we highlight: 1) Integration of AI into Microsoft Power suite® processes to improve tracking report accuracy and efficiency; 2) AI for adjunct faculty continual professional development and support and 3) Privacy considerations to improve efficiency and student learning. For each area, we provide background information and context, benchmarks used to gauge AI integration success, implementation challenges, and lessons learned.

(1) Integration of AI into Microsoft Power suite® processes to improve tracking report accuracy and efficiency

Background Information and Context

One of the IE office's primary tasks was to provide accurate, timely, and comprehensive data to college staff, faculty, and the public for a wide variety of needs and for a wide range of purposes.

Staff and administration, for example, needed to be appraised of semester schedules before the assessment period began and throughout the semester when deadlines approached in accordance with the office's leadership responsibilities in the assessment process. As data was submitted to the office, up-to-date and highly accurate reports were required for timely fulfillment of continual improvement requirements. Public information on the college's demographics, success rates across degrees and courses, and other metrics needed to be available and quickly updated to facilitate data-driven decisions from other units' leadership. This necessitated a large volume of reports and dashboards with varying levels of intricacy and update frequency, all of which needed to be accurate and easily corrected if errors occurred. This large volume presented a substantial burden to our limited IE office staff, as none of the reports were automated and each required manual updating, sometimes multiple times a day from very large volumes of data.

The IE office also had extremely important and complex internal data that needed to be accurately recorded, updated, and presented to meet accreditation requirements. Because the reaffirmation process required so much documentation maintained by a homegrown system, it was absolutely crucial that data and supporting documents were created, tracked, and filed in a way that not only allowed easy assessment of which areas in the reaffirmation report might need more attention in order to pass a review, but also allowed for quick retrieval and integration into the report itself. These internal data experienced a substantial evolution in how they were tracked over the span of the ten-year reaffirmation period, and AI presented a highly desirable opportunity to create efficient and partly automated reports to replace solely manual updates.

Benchmarks Used to Gauge AI Integration Success

The combination of manual data entry, a large volume of reports, and a small IE team led to an effort to automate and streamline the use of AI resources. Around the time of the President's AI Initiative, Power BI® introduced a feature called "Q&A," which allowed users to ask natural language questions and input natural language prompts to explore the data in a report, including automatic generation of calculations, tables, and visuals. The appeal of this feature was that it had the potential to allow staff and faculty to easily retrieve the information and analysis they wanted without IE staff creating a bespoke report. An additional benefit of the natural language functionality was that it had the potential to make data inquiry and analysis more accessible to faculty and staff regardless of their experience with data analytics.

Generative LLMs also presented a unique opportunity to streamline the research, development, and troubleshooting of complex Power BI®, Excel®, and Power Query® functions. This application directly benefitted the individual IE staff members, as they could use LLMs (in this case, ChatGPT®) to brainstorm solutions that were viable in context, then refine the code produced, and finally troubleshoot problems. Using ChatGPT® in this way considerably shortened the time needed to research possible applications and solutions for technical challenges, including many that fell outside of the scope of staff experience and expertise. Tasks that would otherwise have required outside consultation suddenly became possible for a single staff member to tackle in a reasonable timeframe.

Implementation Challenges

At the time of the President's Initiative, PowerBI's® Q&A feature was brand new. One consequence of this newness was that it came with technical limitations, especially in terms of the flexibility of the natural language query aspect. After exploring different possibilities for implementation and testing them within the office, it was determined that using the feature effectively as a non-technical report recipient required a level of expertise and familiarity with data analytics and AI prompt engineering that defeated the intended application of the Q&A feature. However, office leadership bookmarked the feature for potential later implementation if Microsoft® added additional robust natural language support.

Even with highly tech- and data-literate staff within the office using generative AI tools, an entirely new kind of literacy had to be developed: AI literacy. The challenge of prompt engineering was entirely new at the time and even now remains an ever-evolving challenge as LLM applications are updated by their providers. Strong critical thinking skills were required to get good output from the AI service. For highly complex or specific tasks, like assisting with Power BI® DAX code writing, generative AI had to be treated like a useful but frequently inaccurate assistant. Using the AI service enabled staff to learn and use advanced commands and functions that would otherwise have taken prohibitively long times to develop, but extensive problem-solving and debugging was required.

Lessons Learned

Firstly, it became clear that as generative AI came into greater use within the realm of higher education, institutions would benefit greatly from increasing AI literacy in faculty, staff, and students. Increasingly sophisticated AI applications may allow users with less knowledge of and experience in certain fields, such as data science, to get the output they want even without high AI literacy, but that will come with an inevitable tradeoff requiring staff responsible for implementing and maintaining any applications to be highly AI literate. Even with that ease of use, faculty and staff would still benefit from AI literacy in order to bolster their critical thinking and problem-solving skills when it comes to evaluation of the AI's output. Inaccurate output requires correction, and if generative AI is not used thoughtfully then it can increase workload rather than decreasing it.

The second lesson learned from this implementation involved understanding the purpose of technology as potential infrastructure, particularly for small offices with limited resources. Although investing in AI literacy and training was a heavy time investment on the front end of this initiative, the possibilities afforded to this small unit in terms of capacity were multiplied by the potential of leveraging generative AI or other technological tools like Power BI® as ways to automate processes to increase internal efficiency. In higher education administration, particularly in public institutions, this type of capacity building becomes a value-added process in terms of low financial investment and high human resources or personnel return. For example, in this office, the use of generative AI to help create or partly automate reports that were needed for faculty or staff evaluative measures became a mechanism by which to reduce the amount of time manually creating the reports, and dedicate more time to providing professional development support to faculty and staff in understanding the data, and facilitating conversations around continuous improvement practices like the initiative highlighted below.

(2) AI for Adjunct Faculty Continual Professional Development and Support

Background Information and Context

For our second benchmark, our office sought to leverage AI support to generate and enhance resources on campus used for faculty professional development relating to institutional effectiveness and assessment processes. This was a major challenge for our campus as several academic programs utilized a large portion of adjunct faculty to teach general education and other prerequisite courses to satisfy student demand in special admissions programs. These programs, for example, included healthcare specialties which required specific prerequisite courses in biology, anatomy, and physiology to be considered for admittance. Due to their transient nature as temporary faculty at the college, and the nature of the courses that they taught, — which required assessment and data collection for accreditation purposes — this population, and their administrative leadership, was caught within a particular professional development challenge. Each semester a large group of new adjunct faculty needed to be trained in the assessment process and offered continual support to collect data using institutional systems with which they were unfamiliar.

From the IE perspective, the challenge was further complicated by the limited staff and availability to address mounting adjunct faculty concerns, questions, or support requests. This, in turn, resulted in a bottleneck of emails and phone calls during assessment and data collection deadlines throughout the semester. There are several data and assessment implications related to this challenge, including incomplete data, messy data collection strategies, and programs that run into accreditation and compliance issues if support is not provided. Therefore, to address this challenge, our office sought to leverage generative AI to help build practical and continual support for adjunct faculty that could offer added infrastructure during times of high-volume requests.

Benchmarks Used to Gauge AI Integration Success

In conceptualizing this benchmark, we were looking for AI generated supports to potentially field adjunct faculty questions about assessment — whether through chatbots or similar technology — that could help ease the load during these ebbs and flows of the semester. Initial ideas included placing responses to Frequently Asked Questions in generative AI technology infrastructure to help create a chatbot for faculty on campus with the goal of providing 24-hour support during assessment deadlines. In working on this benchmark, we acknowledged that this needed to be a collaborative strategy in two ways: 1) for building the infrastructure, we needed to incorporate IT support and other units to understand how this technology would work with our systems and 2) in building the training guides, materials, and internal infrastructure, we needed to collaborate with faculty and LMS support staff to ensure feasibility of use.

Several initial benchmarks were used to gauge AI integration success for this goal, including collaborative touchpoints. Initially, the IE team leading this charge was tasked with learning more about the technical capabilities of AI in terms of a chatbot or other integration service, and they completed 10 hours of Artificial Intelligence Leadership training within the first month of launching this goal. Next steps included requesting initial launch meetings with personnel from the IT unit leaders to brainstorm pathways on using this technology for adjunct faculty support. These meetings were set to take place twice a month for the duration of the 6-month initiative to discuss progress and try potential pilot studies on the development of chatbot technology using AI. From the faculty collaboration perspective, separate monthly meetings were scheduled to discuss gaps in training and support for adjunct faculty, with updates from the IT and technology team shared as they developed. A proof of concept for this development was intended to be finalized at the end of the 6-month process.

Implementation Challenges

Although initially the momentum to leverage AI to help create a continual faculty support system for adjuncts unfamiliar with the assessment process was strong, these collaborative units ran into two major implementation challenges. The first was related to technological limitations that came with the development of a homegrown chatbot system for adjunct faculty that was compatible with Microsoft® services. Effectively, the College had recently developed a proof of concept of a similar application for Student Affairs units to help their support staff address common student questions and concerns in high volume instances throughout the semester. The technological infrastructure of that system ran through a different platform than that of the College's internal system, which created significant barriers in developing an internal system for faculty use within Microsoft® services.

This, in turn, was relevant to the faculty collaborative challenges we faced which again resulted more in technical conceptual frameworks. When faced with the decision to move to an external platform, it caused the potential risk of losing a professional development foundation that faculty were familiar with and would have lost momentum in terms of knowledge gained in other areas of assessment (i.e., having to train faculty in another system to find necessary supports). In leveraging the same system to integrate AI technology and enhance professional development material that was already available on our internal faculty development platform, we ran into challenges related to permissions, the divide between faculty familiar and unfamiliar with these digital tools, and connectivity issues between the internal platform and the AI support we were hoping to integrate.

Lessons Learned

At the end of the 6-month initiative, we did not reach our benchmark for a transformative chatbot technology based on AI support that could offer continual assistance to adjunct faculty as they navigated the complex institutional assessment process. However, from this experience several lessons were learned in how the different units on campus, and larger areas like IE, IT, and Academic Affairs, function as a technological infrastructure. First, it is interesting to note that, as Mitchell and King (2018) indicated, the mission of postsecondary institutions is primarily to serve students that are enrolled in their academic offerings. However, to this end, as Arney et al. (2023) argued, this cannot be without taking into consideration the role of the faculty in providing these programs. When it comes to technological support, the investments that institutions make to support technology adoptions should consider their benefit to both the student and faculty populations that make up the dynamics of the institutions. In our case, the resources into technological infrastructure were focused on student accessibility and feasibility of use, whereas faculty support was mostly internal and limited in terms of AI integration and development.

However, this led to our second lesson learned from this initiative — investing in skilled IT and data analysts when creating homegrown technological systems with limited resources is key. Despite the limitations faced in creating an actual chatbot system, the IE and IT team were able to develop a parallel professional development platform that housed all the trainings and resources collected as part of the collaborative faculty sessions, which became a cornerstone of the support that adjunct faculty used in incoming semesters. Finally, through these conversations, faculty were able to learn the implications of using AI as part of evolving and complex systems, which led to discussions related to new course offerings for students, including: Applied Artificial Intelligence in Business, Artificial Intelligence Thinking for Computer Science, and the Artificial Intelligence and Ethics course.

(3) Privacy Considerations to Improve Efficiency and Student Learning

Background Information and Context

For our third benchmark, our office leveraged a partnership with the institution's IT unit to better understand and provide parameters for stakeholders regarding privacy and data protection considerations when using generative AI. This was a major challenge for our campus as AI literacy was limited to a few administrative leaders in specific data and technology fields. As use of AI was being encouraged by Executive leadership, faculty and staff alike were engaged in exploratory processes related to new AI technologies and their uses, often not realizing the implications with respect to sharing certain information or data within an AI service. Early in the adoption of AI into faculty and staff workflows on campus, it became apparent that specific parameters relating to guidelines from the Federal Educational Rights & Privacy Act (FERPA) as well as proprietary data integrity and security regulations needed to be conveyed. Most of the messaging from this perspective was initiated by IT through internal electronic communications to act as a stopgap against unintended data security compromises that were common in higher education institutions at the time (Gagliardi, 2022).

To assist in addressing this challenge, the IE office played a specific strategic role by bridging gaps between the appropriate use of student data and engagement with generative AI technology from an IT security lens. Due to existing partnerships with academic leaders (e.g., Deans, Associate Deans, Chairs) and previous professional development opportunities related to student learning data and reporting, this office supported IT efforts to improve faculty AI literacy. These in-depth trainings that were couched in contextual and real-time applications for administrative reporting offered significant opportunities to enhance the protective measures shared by IT professionals on campus. Generative AI therefore played a role in assisting with faculty and staff obligations to complete required reports, while also teaching valuable strategies to consider while engaging with FERPA and data security issues.

Benchmarks Used to Gauge AI Literacy Success

Previously, the IE office had recorded data for learning regarding digital literacy, and therefore had experience with understanding benchmarks related to technology skills. Leveraging this foundation, staff from this office helped faculty and staff to make connections between the digital literacy outcomes that were shared with students and the AI literacy outcomes and skills that were now being required from faculty and staff. These original digital literacy outcomes for students were: Find and Utilize Digital Tools, Use Digital Tools to Create Content, and Use Digital Tools to Share Content. In a similar vein, outcomes related to this Common Digital Literacy Assessment Rubric were adapted for generative AI use and integrated into the professional development trainings for student learning data across campus.

Holistically, through the integration of these direct generative AI trainings into the professional development already being offered for student learning data, it was evident that data security implications were being increasingly accounted for by faculty and staff. A noted benchmark included fewer necessary interventions needed from our collaborators in IT. Further, academic leadership adopted specific AI literacy training to help address faculty concerns with data integrity at the student learning level.

Implementation Challenges

In co-designing the updated professional development training for faculty and staff, it became apparent that disciplinary differences would influence the way in which participants would interpret and apply AI literacy guidelines to their work. For example, Computer Science faculty were attuned to the data security implications of sharing student data with commercial generative AI services and were receptive to learning how to better integrate this technology while accounting for security considerations. Other disciplines, however, were more resistant to using generative AI in any form, which limited the implications of this training for their units.

The other significant challenge in implementing this initiative was the necessity of up-to-date federal and institutional policies regarding the use of generative AI overall. However, because of the newness of this technology in higher education, these policies did not exist as they were being designed as just-in-time guidance, rather than long-term guidance, with respect to security and data integrity challenges. This meant that the partnership we held with IT during this time and the professional development offered were some of the only institutional avenues by which AI literacy was being shared to faculty and staff from an institutional perspective.

Lessons Learned

Higher education institutions will always need to adapt to significant contextual challenges, especially when it comes to technological changes like the availability of commercial generative AI services. However, scholarship notes that higher education institutions often are slow to adapt to such changes due to the reification of organizational structures and limits to infrastructure (Arney et al., 2023). One major lesson from this initiative was that the sooner leadership decides that an issue needs to be addressed, the sooner an institution can decide on a comprehensive solution or solutions. For this challenge, as it was related to security concerns, our institutional leadership acted quickly and identified a taskforce to address this issue.

Another important lesson learned related to this initiative is that a general institutional level resource is an effective solution for a variety of stakeholders. For example, after a few months of implementing these professional development trainings in tandem with IT, the institution provided upper-level guidance on which service was appropriate to use concerning student data and other security considerations. As an institutional-level solution, Enterprise subscriptions to most generative AI services provide total protection of any data, proprietary or otherwise, that institutional users input into that service. Enhanced by the AI literacy trainings, this solution allowed faculty and staff to safely use generative AI on proprietary data while also aligning and complying with all legal regulations.

Implications

Implications from this contribution speak to AI-enhanced institutional research and strategic planning capacities, specifically for smaller IE offices and administrative units that can lean on AI as a tool for capacity building and resource allocation. The following will explore these implications from decision-making, efficiency, and leadership connections.

Decision-Making

The AI Professional Development Initiative, as a 6-month trial to spur innovation and leadership in the area of AI understanding and use, was on the whole an effective practice in adaptative leadership and management. By allowing all areas on campus to instigate change based on perceived challenges and how this new technology could be leveraged as a tool to help support change, rather than foster disruption, not only did our staff become more intimately aware of how this technology works, but we were also able to identify ways in which to leverage it more effectively within our unique contexts. Scholars indicated that through adaptive leadership practices, “Workers may gain knowledge from one another through workplace social interactions by exchanging anecdotes and insights that encourage risk-taking, creativity, and the pursuit of novel solutions” (Chughtai et al., 2023, par. 3). Through internal team meetings related to decision-making processes using AI within the units, as well as through the reports and presentations shared with other campus leaders in the larger AI Professional Development Initiative, it was evident that risk-taking and creative decisions related to using this new technology were being implemented in various capacities across campus, more so than if the larger AI initiative were not in place.

Efficiency

In terms of capacity building, leveraging AI as a tool to help facilitate the integration of processes to impact the efficiency of services was evident in our first initiative, whereas using AI to create new infrastructure, as demonstrated in our second initiative, was less effective. In terms of our third initiative, for example, which focused more on the applications of AI with respect to use by faculty and staff for assessment purposes, the initiative provided insights on processes and parameters that needed to be taken into consideration to comply with privacy practices at the institutional and state levels. Connecting back to adaptive leadership strategies, the lessons learned from this initiative highlight the need to promote an organizational culture of continuous learning as it required reflection and needs assessments in different areas to better understand the capacities and limitations of AI use when applied to staff or faculty processes, promoting efficiency and understanding among units (Chughtai et al., 2023; Nelson & Squires, 2017). In this sense, this larger AI Professional Development Initiative highlighted change as an opportunity for growth through understanding continuous improvement mechanisms which align with efficiency processes to improve outcomes.

Leadership

According to Heifetz et al. (2009), “Adaptive leadership is the practice of mobilizing people to tackle tough challenges and thrive” (p. 14). True to the adaptative leadership framework, the AI Professional Development Initiative allowed for an analysis of the technical and adaptive challenges needed to create change from multiple leadership perspectives. To clarify, Northouse (2022) summarizes that the adaptive leadership strategies originally introduced by Heifetz and colleagues (2009) account for three types of challenges: technical, adaptive, and both technical and adaptive. Technical challenges are problems that are clearly defined with known solutions through organizational procedures, whereas adaptive challenges are not clear-cut or easy to identify. However, both technical and adaptive challenges are considered those that are clearly defined, but do not have a clear solution. If higher education allows for drastic technological changes to happen without clear organizational leadership to anticipate organizational and behavioral changes, from an adaptive perspective, it lessens the probability of initiatives being effective and heightens the probability of change being not well received (Northouse, 2022). To this end, there is a larger implication to be considered as higher education institutions reckon with the ever-changing technological landscape and what this means for the survival of traditional or innovative processes (Nelson & Squires, 2017).

Conclusion

In this contribution we focused on a case study that centers on an IE office and three areas that were impacted by an AI Professional Development Initiative. This particular initiative demonstrated an adaptive leadership strategy (Northouse, 2022) that was intended to preempt the overwhelming influence and potential concerns related to generative AI use in higher education. Specifically, the purpose of this initiative was to better understand how this new technology could support effective administrative decision-making processes for overall institutional growth. As part of this IE case study, we provided context related to the institution and the initiative, and explored each area impacted in the IE office through four related sections: (1) background information and context, (2) benchmarks, (3) implementation challenges, and (4) lessons learned.

Implications from this case study were provided in connection to decision-making, efficiency, and leadership with respect to adaptive leadership strategies. Leveraging lessons learned from this case study, we underscore the need to implement prompt leadership decisions, provide right-in-time resources — like AI literacy, enterprise subscriptions, and professional development support — in order to promote efficiency with respect to use of these types of technologies, specifically for smaller units servicing large student or faculty populations. Moreover, adaptative leadership strategies, like the ones adopted in this case study, promote collaboration and the use of existing relationships in institutions as a way to build existing capacities, but also identify areas where this type of technology can become a vital resource or assistant. In tandem with adaptive leadership philosophy, this initiative illustrated that there needs to be motivation to empower others to contribute collective expertise, provide opportunities for growth, and drive success through identifiable change (Chughtai et al., 2023; Rachmad, 2022). At the end of the day, addressing complex challenges like technological shifts cannot be a solitary executive pursuit and must include collaboration from all institutional leaders in order to go from pilot to practice.

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Journal of Higher Education Management, 41(1), 40-54 (ISSN 2640-7515).

Streamlining Curriculum Design for Programmatic Coherence and Faculty Workload Distribution through AI

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Abstract

As AI tools become more accessible in higher education, academic leaders face the challenge of integrating them strategically to advance institutional priorities. This study presents a leadership-driven approach to using generative AI for curriculum alignment and faculty workload distribution within a graduate nursing program. By leveraging NotebookLM, ChatGPT, and Fliki, academic teams can align learning materials and assessments to course and program outcomes, ensuring curriculum coherence, accreditation readiness, and reduced faculty burden. Rather than automating teaching, the integration of AI enhances institutional oversight and fosters equitable workload practices, offering leaders a pathway to support scalable course design and institutional goals.

Keywords: Generative artificial intelligence, curriculum alignment, faculty workload, AI-assisted instructional design, nursing education leadership

Introduction

As artificial intelligence (AI) tools grow increasingly accessible in higher education, the challenge for academic leaders is no longer simply whether to adopt generative AI (GAI), but how to do so strategically, ethically, and in ways that support institutional goals (Sposato, 2025). This case study contributes to that evolving conversation by presenting a leadership-driven framework for integrating GAI into curriculum alignment and faculty workload distribution within an online graduate nursing program in Hawaiʻi. For academic leaders overseeing online and in-person programs, transparent alignment among program and course learning outcomes, instructional materials, and measurable assessments is essential, not only to uphold instructional quality, but also to ensure accreditation and curriculum coherence. This need is especially pressing in nursing education, where institutions are transitioning to the competency-based *Essentials* framework across curricula (AACN, 2021), and where recent research has demonstrated the complexity of curriculum redesign required for this shift (Dormire et al., 2025). Without centralized support, however, alignment efforts often result in inconsistency, duplicated efforts, and uneven faculty workload, factors that intensify the national nursing faculty shortage.

Accordingly, this study examines how generative AI tools can be leveraged by instructional designers and nursing curriculum teams to create outcome-aligned courses and reduce faculty workload. NotebookLM, a knowledge synthesis and organization platform, was applied first to map program, course, and module learning outcomes, and then to generate draft assessments anchored in aligned instructional materials including syllabi, readings, lectures and multimedia. ChatGPT was then employed to refine and enrich the draft assessments and to generate instructional video scripts based on the aligned readings and activities, ensuring variety, engagement, and continued fidelity to the course and program learning outcomes. Fliki, a GAI video platform, extended this process by producing short, outcome-driven topic overview videos using the previously generated script, providing students a consistent weekly overview directly tied to assessments and readings. From a leadership perspective, this centralized design model not only strengthens accreditation readiness but also supports the graduate program's practice of developing standardized course curricula that are centrally designed and then replicated across multiple sections each term. In this way, faculty are relieved of repetitive course-building tasks and can devote more time to higher-order teaching, mentoring, and feedback.

This approach to GAI tools offers multiple advantages. It ensures curriculum fidelity, enhances oversight, promotes equity in workload, and strengthens readiness for accreditation through clear alignment of content, assessments, and intended outcomes. In nursing education, where faculty burnout and resource constraints persist, such strategies sustain program quality while supporting retention and student success. When used thoughtfully, GAI extends rather than replaces human expertise, becoming a collaborative partner in advancing institutional excellence and preparing practice-ready graduates for safe, effective patient care.

To this end, this study aimed to examine how generative AI tools can be integrated into graduate nursing education to address leadership priorities related to curriculum coherence, equitable faculty workload, and program readiness for competency-based nursing education. Guided by these priorities, the following research questions structured the study: (1) How can generative AI tools (NotebookLM and ChatGPT) be integrated into a backward design process to align module, course, and program learning outcomes, thereby strengthening curriculum fidelity and preparing programs for competency-based education? (2) In what ways does the use of generative AI in course design affect faculty workload equity and promote consistency across multiple course sections? (3) How do student perceptions of content alignment, assessment design, and instructional videos differ between sections that received AI-aligned assessments with Fliki-generated overview videos and those that received only the aligned assessments?

Literature Review

Curriculum Alignment as a Foundation for Nursing Education

Curriculum alignment and accreditation have long been central to nursing education. Biggs' (1996) theory of constructive alignment emphasizes the intentional integration of learning outcomes, teaching strategies, and assessments to promote coherence and accountability in higher education. In this context, curriculum alignment has been described as a cornerstone of nursing education, ensuring that competencies and professional values translate consistently into course outcomes and assessment practices (Khan & Salim, 2015). More recently, schools of nursing have engaged in program-wide alignment projects to align curricula across degree levels, often in response to national competency frameworks such as the AACN's *The Essentials: Core Competencies for Professional Nursing Education* (2021; Nowak et al., 2024).

While alignment has traditionally relied on faculty expertise and administrative coordination, emerging studies demonstrate how GAI can assist in streamlining curriculum development and maintaining fidelity to competency frameworks. In a case study of an industrial engineering and management program, Padovano and Cardomane (2024) utilized GAI as a design assistant to analyze large and complex curriculum datasets to assist in the development of a competency-based curriculum. Their work highlighted GAI's potential to streamline time-intensive aspects of curriculum development while ensuring alignment with competency frameworks. Similarly, Squalli et al. (2024) integrated design thinking, constructive alignment, and GAI to design a first-year medical curriculum in Morocco, showing how structured GAI-assisted instructional design methods can foster innovation while ensuring curriculum coherence. As these studies show, curriculum alignment is not only a pedagogical necessity but also a leadership responsibility, requiring administrative structures that promote coherence and accountability.

Faculty Workload Pressures and Burnout in Nursing Programs

For leaders in nursing education, persistent workload distribution challenges create barriers to recruiting, retaining, and equitably supporting faculty. Administrators struggle with disparities between academic and clinical salaries, rising accreditation expectations, and increasing student demand. Program leaders describe relying on adjunct faculty, often teaching outside their specialties, and managing continuous cycles of onboarding that strain workplace climate and morale (Jarosinski et al., 2022). Moreover, faculty burnout is widespread. Zangaro et al. (2023) reported that more than 85% of nursing faculty experience moderate to high levels of exhaustion and disengagement, while Anderson et al. (2024) found unrealistic workload and low compensation to be leading reasons faculty consider leaving academia. These are pressing issues not only for faculty well-being, but also for institutional sustainability and student success.

Artificial Intelligence and Academic Leadership in Higher Education

The integration of GAI into higher education presents both opportunities and challenges for addressing leadership concerns related to workload distribution, faculty burnout, and sustainability. Sposato (2025) developed a taxonomy of AI applications in higher education leadership, identifying domains from administrative efficiency to ethical AI governance. Within this framework, GAI has potential to optimize workload distribution by automating routine tasks such as scheduling, grading, and compliance tracking, freeing faculty for higher-order teaching and mentoring. Katsamakas et al. (2024) further note that GAI is not simply an efficiency tool but a driver of institutional transformation, reshaping decision-making and resource allocation. Given the rapid advancement of GAI tools in professional activities, the intersection between GAI and education has expanded dramatically, creating new leadership responsibilities for faculty and administrators in guiding how learners at early stages of professional preparation engage with these tools (Ruano-Borbalan, 2025). For administrators, this positions GAI as both a technological and organizational tool requiring careful leadership.

AI for Curriculum Design and Assessment Alignment

In the field of curriculum design, GAI is increasingly tested for its ability to create aligned instructional materials and assessments. Choi et al. (2023) and Lee (2025) demonstrate how tools such as ChatGPT can design learning activities and assessment items mapped to specified learning outcomes. Additionally, Ilieva et al. (2025) propose a framework for GAI-driven assessment development that ensures validity, transparency, and fairness. At the same time, scholars caution that the benefits must be weighed against concerns. As reported by Lane et al. (2024), GAI can serve as both a tool and a tyrant, offering efficiency and innovation while raising challenges related to transparency, ethical use, and AI literacy. Labrague et al. (2024) and Gunawan et al. (2024) recommend that although GAI technologies enhance aspects of student learning and teaching, faculty must also acknowledge the limitations. As these findings suggest, a balanced perspective is essential. While GAI offers efficiency, alignment, and creativity, its integration must be paired with ethical safeguards and thoughtful instructional design. As discussed by Montejo et al. (2024) and Lifshits (2024), a comprehensive multimodal educational approach combining innovative learning strategies with explicit attention to ethics has potential to support the responsible integration of AI concepts into nursing curricula.

Ethical and Human-Centered Approaches to AI Integration

Alongside practical applications, scholars have investigated ethical and human-centered implications of GAI use in higher education. Malone (2024) cautions that while GAI can support instructional design, it raises concerns about who owns instructional materials, whether GAI-assisted grading processes are transparent to students, and whether automated evaluations are applied equitably. According to Polat et al. (2025), shared leadership is a leadership model grounded in dialogue and cooperation, informed by interdisciplinary perspectives and recommended when addressing the ethical dimensions of GAI integration. Kim et al. (2025) found mixed perceptions of GAI in nursing education, with participants emphasizing the importance of keeping the human-centered values of nursing at the forefront. Li et al. (2025) address these concerns through the ARCHED framework, which promotes Accountable, Reliable, Clear, Human-centered, Explainable, and Data-driven GAI adoption. Similarly, Stefaniak and Moore (2024) highlight the potential for GAI to support inclusivity in course design, provided administrators maintain oversight to prevent bias and exclusion.

Building on these findings, additional empirical studies highlighted related challenges. Bahroun et al. (2023) identified transparency, equity, and long-term impact as recurring concerns in GAI integration, while Eminoglu and Celikkanat (2024) found a significant relationship between nurse leaders' self-efficacy and medical AI readiness, suggesting that confidence in guiding teams and change management is essential for responsible adoption. These frameworks reinforce the role of academic leadership to balance efficiency with a commitment to ethics, inclusivity, and human-centered decision-making.

Implications for Nursing Education Leadership

For nursing education in particular, the shift toward competency-based curriculum development, workload strain, and the rapid rise of GAI presents a significant juncture for leadership decision-making. On the one hand, GAI is promising for reducing faculty burnout, ensuring consistency across multiple course sections, and generating outcome-aligned assessments and instructional materials. On the other hand, leaders must navigate the challenges of ethical adoption, faculty readiness, and maintaining the human-centered values of nursing education. Promoting responsible implementation in nursing education requires a clear articulation of expectations. Nurse educators can guide and guard the use of GAI by modeling ethical practices and aligning adoption with professional standards (Lane et al., 2025). As such, for academic leaders, the task is not only to adopt GAI tools strategically, but also to ensure that their integration aligns with institutional missions, accreditation standards, and the well-being of faculty and students alike.

AI Readiness in Nursing Education

AI readiness in nursing education is often questioned, and the adoption of tools for teaching, learning, research and clinical practice requires thoughtful consideration for both faculty and students. Faculty readiness involves awareness, skills, mindset and ethical literacy, while student readiness involves critical thinking, digital literacy, professional judgement, and ethical use. As research has demonstrated, nursing students' frequent use of GAI technologies and prior experience influence their learning (Taskiran, 2023), demonstrating the responsibility of faculty and academic leaders to adapt curricula accordingly. Curriculum reform, therefore, requires integration of evidence-based experiential learning approaches such as simulation and case-based learning, updated evaluation methods and embedding AI related competencies (Simms, 2025). AI also supports research-related activities, including analyzing health data and evaluating AI-supported systems (Hwang et al., 2022). Integrating 15 studies, GAI has shown significant potential to improve skill training, enhance student engagement, and foster communication skills in nursing education (Ma et al., 2025). Ensuring readiness therefore requires not only technological adoption but also structured processes of curriculum reform and leadership oversight, themes explored in the present study.

Methods

Research Design

This study employed a qualitative descriptive case study design with quasi-experimental elements, using a leadership-driven approach to integrating generative artificial intelligence (GAI) into curriculum alignment and faculty workload distribution within a graduate nursing program. Conducted during an eight-week term, the study focused on four sections of an online course taught by two faculty members, one of whom also served as the PMHNP program coordinator and co-author. The project explored how GAI tools supported outcome-driven curriculum design through a backward design process aligning program, course, and module learning outcomes with instructional materials and assessments. Specifically, the study examined the use of NotebookLM (a knowledge synthesis and organization platform), ChatGPT, and Fliki (a GAI video-generating platform).

Beyond GAI's role in curriculum alignment, the study also investigated its potential to reduce faculty workload and promote consistency across multiple course sections. A further aim was to ensure program readiness for competency-based education guided by national frameworks such as the AACN's *The Essentials: Core Competencies for Professional Nursing Education* (2021). The pilot course therefore served as an initial model for how academic administrators can strategically guide GAI adoption to ensure curriculum fidelity, promote equitable workload distribution, and sustain program quality at scale.

The quasi-experimental component of the study compared two groups. Two sections received GAI-aligned assessments supplemented with Fliki-generated topic overview videos, while the other two sections received only the GAI-aligned assessments. Students were not aware of section differences at the time of enrollment, which functioned similarly to random assignment and provided a natural comparison of student perceptions of content alignment, assessment design, and, when applicable, GAI-generated instructional videos.

Setting and Participants

The pilot was situated within a Master of Science in Nursing program at a private university in Hawaiʻi. The course was chosen because it is central to the program's Psychiatric Mental Health Nurse Practitioner (PMHNP) track and was already scheduled for a curriculum refresh. Four sections of the course were offered during the term and taught by two faculty members, including the program coordinator. Across the four sections, 56 students were enrolled, 31 in the two sections that included weekly Fliki-generated topic overview videos and 25 in the two sections that did not. This course provided a strategic opportunity for program leadership to evaluate how GAI-supported design could strengthen fidelity across sections and advance the shift toward competency-based education in nursing. It also provided a context for examining how GAI integration might promote equity in faculty workload.

Data Collection

Data from multiple sources were collected to capture student perceptions of content alignment, assessment design, and GAI-generated instructional videos, as well as of the curriculum design process.

Course Evaluations

At the end of the term, students were requested to complete the course evaluation, which is sent by the Office of Institutional Research every term. The evaluation includes 21 closed-ended items based on a 5-point Likert-type scale, and two open-ended items. The closed-ended items focus on course materials, workload, engagement, learning outcomes, and instructor qualities. Students can choose from five responses including *Very Good* (5), *Good* (4), *Adequate* (3), *Poor* (2), and *Very Poor* (1). The two open-ended items provide an opportunity for comments on course strengths and recommendations for improvements.

Across the four sections, 18 students completed the evaluations, representing 32.1% of total enrollment. In the two sections that incorporated Fliki videos, 35.5% of the students (n=11) completed the course evaluation, and 28% of the students (n=7) completed the evaluation in the non-Fliki sections.

Curriculum Design Process

Data on the GAI-assisted curriculum design process were collected from institutional documents including program learning outcomes (PLOs), course learning outcomes (CLOs), and module learning outcomes (MLOs), as well as course syllabi, lecture transcripts, and assigned readings. Additionally, records of GAI interactions including NotebookLM prompts, ChatGPT refinements, generated outputs, and researcher notes documented the alignment workflow.

Data were collected during four iterative phases. During the first phase, NotebookLM was used to map learning outcomes at the module, course, and program level. Although curriculum mapping had previously been conducted during the original course development, the curriculum refresh provided an opportunity to re-examine the efficacy of GAI-assisted alignment. As with the other three phases, GAI prompts and the corresponding GAI outputs were documented.

During the second phase, the instructional designer and the PMHNP program coordinator, who also served as the faculty subject-matter expert, used NotebookLM to generate draft assessments aligned with the module and course learning outcomes as well as the weekly readings. These drafts were refined with ChatGPT to enhance variety, creativity and engagement while confirming outcome fidelity. During the third phase, ChatGPT was utilized to generate concise instructional video scripts aligned with the assessments and readings. All GAI-generated products were reviewed by the program coordinator.

During the last phase, the finalized scripts were imported into Fliki to generate weekly topic overview videos that connected learning outcomes with readings and assessments. Additional text was embedded in the video scenes to provide multiple means of representation, and images were edited to mitigate bias in GAI-generated content. The student evaluation data served as additional feedback to assess perceptions of curriculum design process and its effectiveness including differences in incorporating GAI-generated Fliki videos or not.

Data Analysis

The Likert-type scale responses from the course evaluation were analyzed descriptively, with means calculated from the 5-point scale (*Very good* = 5 to *Very Poor* = 1) to identify patterns in how students perceived course materials, assessments, workload, engagement, and achievement of learning outcomes. Given the small sample size, these findings were used for exploratory insights and described qualitatively. Open-ended responses were analyzed thematically, focusing on student perceptions of content alignment, assessment design, and GAI-generated instructional videos.

Additionally, the quality of GAI as a curriculum alignment tool was analyzed using document analysis. To strengthen trustworthiness, triangulation across institutional documents such as program and course learning outcomes and syllabi, GAI outputs, and course evaluation data was implemented. The analysis was reviewed collaboratively by the program coordinator, the Dean of the School of Nursing, and the instructional designer ensuring multiple perspectives on accuracy, alignment, and leadership implications.

Ethical Considerations

This study was reviewed as an educational quality improvement project, and IRB approval was received. All course evaluation responses were anonymous and no identifiable student data were used. The dual role of the program coordinator as both instructor and co-author was explicit with co-authors serving to mitigate potential bias. Accordingly, this research reflects the broader ethical responsibilities of academic leaders in overseeing GAI adoption including student privacy and transparency in how GAI tools are used, while piloting innovative practices to support faculty workload and curriculum fidelity.

Findings

Analysis of student evaluations across the four sections of the PMHNP course revealed notable differences between the two sections that incorporated Fliki-generated topic overview videos and the two that did not. This section begins with a presentation of the quantitative findings from the closed-ended responses, followed by the qualitative findings from the open-ended responses, and a comparative review. The section ends with an overview of the outcomes from the GAI-assisted curriculum design process.

Course Evaluation: Quantitative Findings

In the two sections that integrated GAI-generated Fliki videos, students rated the appropriateness of learning materials positively (M = 4.6 and 3.8), and the effectiveness of resources for engagement very positively (M = 4.9 and 4.5). Ratings of key learning outcomes were consistently very positive in one section (all ≥ 4.5) and moderately to positively in the other (3.8–4.3 range). The overall course recommendation was very positive in both sections (M = 4.9 and 4.7).

The non-Fliki sections showed more variability. Students rated learning materials positively overall (M = 5.0 and 4.3), while scores for engagement ranged from very positive (5.0) to positive (4.0). Ratings of learning outcomes ranged from very positive in one section (≥ 5.0) to moderately positive in the other (3.4–4.0). The overall course recommendation was very positive in one section (5.0) but only moderately positive in the other (3.6), yielding a combined average of 3.8.

Course Evaluation: Qualitative Findings

Open-ended responses provided further insight into these contrasts. In the Fliki sections, students praised the overview videos as “succinct and direct,” contrasting them with prior courses’ lengthy lectures. They highlighted the clear alignment of assessments with objectives, noting the course as better designed and more purposeful than earlier PMHNP courses. Several linked the materials and assessments to confidence in licensure preparation.

In the non-Fliki sections, students pointed to the absence of short video overviews, stating that such videos would have helped guide weekly learning and exam preparation. While some students valued the clinically relevant content, others perceived weaker connections between course materials, assessments, and outcomes.

Course Evaluation: Comparative Findings

Overall, the sections that integrated Fliki videos demonstrated more consistent ratings, with student perceptions generally falling in the positive to very positive range across learning materials, engagement, learning outcomes, and overall course recommendation. Engagement, in particular, was rated very positively in both Fliki sections. In contrast, the non-Fliki sections showed greater variability. While some ratings reached the maximum (5.0), others were notably lower, especially for learning outcomes and overall course recommendation. This suggests that the integration of Fliki videos may have contributed to a more consistently positive student experience, whereas the non-Fliki sections produced more uneven perceptions.

Analysis of the open-ended responses further suggests that sections with Fliki videos benefited from clearer alignment between content, assessments, and outcomes, with students perceiving improved clarity and preparedness. Sections without the videos highlighted precisely those elements including a desire for short overviews, clear guidance, and organized materials.

Instructional Design Outcomes

The GAI-assisted curriculum refresh demonstrated positive outcomes in alignment, assessment design, and faculty workload. Using NotebookLM, course learning outcomes were successfully mapped upward to program learning outcomes and downward to module-level outcomes, producing clear documentation of outcome alignment across the course. ChatGPT refinements enhanced the variety and creativity of assessment drafts, while maintaining fidelity to mapped objectives. Faculty reflections noted that this iterative process reduced the time required to produce aligned assessments compared to prior course builds, lessening workload during the refresh.

The integration of Fliki videos represented the final stage of this design process. Concise scripts generated through ChatGPT and translated into short topic overview videos provided a standardized orientation to weekly content which was noted by students. This ensured consistency across sections and allowed faculty to focus their instructional efforts on higher-order teaching and feedback rather than repetitive content delivery. These design outcomes demonstrate how GAI can serve as a collaborator in instructional design while strengthening alignment to program outcomes.

Discussion

This study exemplifies how GAI can be strategically integrated into course and program design to address leadership priorities of curriculum coherence, workload distribution, and program readiness. The benefits of aligned course design were visible across the sections. Additionally, the need for aligned instructional support such as through Fliki videos was notable as seen in the responses of the two sections that integrated these topic overview videos. The comparison of course sections revealed that students in Fliki-supported sections experienced clearer alignment between materials, assessments, and outcomes, with the videos enhancing the experience of the relevance of the module design and preparedness.

In contrast, students in sections without video support pointed to those very elements including a desire for instructional overviews and stronger guidance. These findings coupled with the documented instructional design outcomes suggest that GAI-assisted processes can reduce faculty burden when producing more coherent, competency-based learning experiences for students. These findings align with a study by Chang et al. (2024) which demonstrated how incorporating GAI into course design improved instructional efficiency by scaffolding assignments, aligning assessments with course and program learning outcomes, and reducing time spent on repetitive design tasks. They emphasized that GAI tools were most effective when used to generate initial drafts which were then refined by faculty. Regarding leadership, the findings of this current study highlight the importance of incorporating GAI not as a replacement for faculty expertise or curriculum teams, but as a collaborator in ensuring program quality, supporting accreditation demands in nursing education, and fostering consistency across multiple sections. In sum, oversight remains integral for academic integrity.

Lessons for Higher Education Leaders

The findings from this pilot highlight that GAI can meaningfully contribute to curriculum alignment and workload distribution, but a strategic approach to adoption is needed. For academic leaders, this includes the importance of utilizing GAI not as a shortcut, but as a strategic partner in ensuring program quality, supporting faculty capacity, and preparing students for competency-based education. This institutional imperative reflects trends across higher education. A national survey of more than 200 leaders and faculty reported widespread enthusiasm for AI adoption but revealed that few institutions had established clear priorities or safeguards for implementation (Grammarly, 2025). The study noted that while nearly 80% of respondents expressed positive attitudes toward AI in the classroom, fewer than half believed their institutions had implemented responsible use measures effectively. As can be seen, enthusiasm alone is insufficient without intentional planning, clear policies, and sustained oversight.

Practical Steps to Implement AI-Supported Curriculum Alignment

Several practical steps can guide leaders adopting GAI-assisted instructional design. Once program goals and graduate competencies are identified, curriculum documents such as syllabi and curriculum maps need to be gathered. GAI tools can then map course-level outcomes to program outcomes, confirm prior alignment, and flag redundancies or gaps. Outputs are refined through iterative prompting by instructional designers or curriculum teams, with faculty validating accuracy and relevance. Courses are then redesigned as needed. When applied systematically, this process strengthens alignment within individual courses while also creating coherence across programs, supporting fidelity and accreditation readiness.

Guidelines for Ensuring Ethical, Inclusive, and Faculty-Engaged Use of AI

Ethical GAI adoption requires an institutional commitment to equity and inclusivity. Leaders must continue to support faculty development, faculty and staff well-being, and student readiness, ensuring that innovation drives growth. Regular evaluation of impact on both learning outcomes and faculty workload is essential. Additionally, it is recommended that AI policies and guidelines be established collaboratively as a shared institutional and program-specific project. As De Gagne and Hwang (2023) argue, nursing education in particular benefits from grounding such guidelines in the five ethical principles of autonomy, beneficence, nonmaleficence, justice, and explicability, which provide a roadmap for ensuring that AI integration both protects learners and strengthens the humanistic values of the profession.

The Role of Leadership in Promoting Sustainable Innovation

Sustainable AI adoption depends on the vision and culture set by academic leadership including clear and ethically grounded objectives for adoption, supported by realistic resource planning. In a culture of continuous learning, experimentation is encouraged, challenges are reframed as learning opportunities, and inquiry is modeled at the leadership level. Accordingly, it is essential leaders ensure that GAI enhances rather than replaces human work, positioning faculty and staff as central to quality assurance. Finally, AI adoption requires adequate time, funding, and evaluation, making thoughtful planning essential for sustainability.

Limitations

While these findings demonstrate the value of GAI at the institutional and course level, several limitations apply. To start, the course evaluation response rate was limited (32.1%) with uneven participation across the sections, limiting generalizability. The study also took place within a single program and course, narrowing the scope of the findings. Nevertheless, these constraints highlight a valuable consideration for academic leadership to draw on multiple sources of evidence when evaluating innovations like GAI such as curriculum mapping artifacts, faculty and instructional designer input, and accreditation requirements.

The study also revealed limitations in the GAI tools themselves. NotebookLM proved useful for mapping outcomes and generating aligned assessments, but its outputs often required substantial refinement. Assessment items had to be reformatted, distractors frequently lacked quality, and references had to be removed from uploaded materials to prevent misinterpretation. Additionally, chat histories were easily lost if not properly saved, and Word documents had to be converted to PDF files before use. While NotebookLM ensured fidelity to outcome alignment, the key factor in its selection, ChatGPT served to refine assessments.

Fliki offered efficiency and quality in producing instructional videos, but its image generation revealed consistent bias. Default imagery frequently overrepresented white men, while women were often depicted as unrealistically thin, resulting in narrow portrayals that excluded diverse populations on multiple levels. When applied to mental health topics such as mood disorders, images tended to exaggerate or stigmatize conditions. These shortcomings highlight the need for faculty oversight in editing and supplementing GAI outputs to ensure inclusivity, accuracy, and professional appropriateness. Student experiences in other contexts reinforce this need. Shen et al. (2025) found that while nursing students viewed GAI tools as highly efficient in organizing case data and streamlining care planning, they also reported frequent errors, limited emotional understanding, and privacy concerns. As emphasized by Shen et al., iterative prompt engineering is essential to improve accuracy and relevance.

For academic leaders, these limitations reinforce a human-centered approach to AI adoption. Rather than assuming GAI can produce final products, institutions can plan for faculty engagement in prompt generation, review, editing, and contextualization. Doing so not only protects program quality and equity but also ensures that GAI serves as a tool to enhance, rather than replace, faculty expertise.

Conclusions

This pilot demonstrates that the integration of generative AI tools such as NotebookLM, ChatGPT, and Fliki into curriculum alignment processes can meaningfully enhance program coherence, reduce faculty workload, and strengthen program readiness for competency-based education. Student feedback reinforced these benefits. Aligned assessments were well received, and the sections supported with Fliki videos stood out as clearer and more consistent.

Completing the full cycle from outcome mapping with NotebookLM, to assessment refinement with ChatGPT, to instructional video generation with Fliki, ensures coherence and consistency across the curriculum. Moreover, GAI has the potential to reshape curriculum design and faculty workload management in ways that improve both quality and efficiency. With the right tools, GAI can scan syllabi, outcomes, and accreditation standards to identify gaps, redundancies, and misalignments. In addition, GAI tools can support competency-based learning by scaffolding modules to follow student progression, generate content and competency-relevant practice cases, and reduce grading burden through rubric development and assessment support.

For leaders in higher education, these possibilities demonstrate the importance of human-centered leadership in guiding GAI adoption. Sustainable use requires intentional oversight, clear alignment with program outcomes, and a commitment to ethical and inclusive practices. In nursing education, where teaching is rooted in compassion, empathy, and human connection, leaders have a particular responsibility to ensure that GAI strengthens caring. This includes practicing transparency, listening, and shared decision making in GAI adoption. Ultimately, trust and oversight are critical to ensuring that GAI serves as a partner to faculty, not a replacement, supporting innovation that advances both student learning and institutional goals while protecting the core values of the discipline. Shared leadership is the key.

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Journal of Higher Education Management, 41(1), 55-60 (ISSN 2640-7515).

Using AI as a Source of Inspiration for Restructuring Departments

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Abstract

Facing challenges such as declining enrollment, reduced funding, and shifting perceptions of the teaching profession, a large, public R1 university in North Carolina undertook a strategic restructuring of its College of Education beginning in the 2024-2025 academic year. Aimed at lowering costs, boosting faculty productivity, and redesigning leadership roles, the process leveraged AI tools like ChatGPT-4 and Gemini 1.5 Pro to model department consolidations and propose new leadership frameworks. This led to reducing departments from six to four and creating a three-tiered leadership support system. This case illustrates how AI can inspire and facilitate organizational transformation in higher education by providing data-informed modeling and neutral structural suggestions.

Key Words: AI, Leadership, Higher Education, Organization

Introduction

Many institutes of higher education (IHE), particularly Colleges of Education (COE), are facing very difficult circumstances. In the state of North Carolina (NC) for example, COE are battling low enrollment due to the *enrollment cliff*, hikes in tuition, low teacher wages, and public discord over the teaching profession (Copley & Douthett, 2020; Fulton, 2025; North Carolina Association of Educators, 2024). Moreover, changes in federal funding distribution and the current attempts to dismantle the Federal Department of Education have also wreaked havoc on the ability for many COE to maintain the support they need to train future teachers (Fernandez, 2025). The constriction of federal funds not only impacts COE but also how local public-school systems can support existing and beginning teachers (EdNC, 2024).

National Trends for Restructuring University Structures

For IHEs, drastic organizational changes are occurring to compensate for fewer federal funds and students (Attridge & Johnson, 2025). Indiana public IHEs are an example of the great lengths taken to consolidate and restructure. Indiana IHEs have cut or consolidated over 400 programs across six of their institutions, with 116 degrees being impacted at Indiana University Bloomington alone (Schwartz, 2025). Such changes are forcing many COE, particularly in NC, to restructure in ways that redefine faculty and leadership roles, reducing the number of faculty/staff, and increasing workloads while having access to fewer resources.

Given the national and statewide issues IHEs are facing, our College of Education began exploring and engaging in discussions for restructuring. There were four primary Goals driving this process:

Goal 1: a reduction in costs (e.g., fewer administrators and adjunct instructors)
Goal 2: the need to increase student credit hour production across faculty
Goal 3: elimination or the redesign of low enrolled degrees/programs
Goal 4: restructure of leadership roles across the college.

As such, during the 2024-2025 academic year the College of Education's leadership team (Team), including Department Chairs and Assistant/Associate Deans, were tasked with proposing ideas to make this possible. Goals 2 and 3 required the team to manually analyze historical enrollment data, faculty teaching loads, and licensure/accreditation requirements to develop effective curricular redesigns. However, the team used AI to assist with Goals 1 and 4. The following case is a brief narrative describing the process used, including examples of AI as a mechanism to support the restructuring of departments and the reimagining of the roles/duties for departmental leadership.

Using AI to Support a COE Restructure: The Process

The College's faculty were distributed across six academic departments that collectively supported a broad portfolio of undergraduate, graduate, and doctoral programs. Prior to the restructuring, the College offered 18 undergraduate degrees, 20 graduate degrees, and operated the state's largest online alternative licensure program. Six academic departments were led by department chairs, while programs and centers were overseen by program coordinators, directors, and specialized research and outreach personnel. The College also housed multiple centers, including the Rural Education Institute, The Irene Howell Assistive Technology Center, and the Center for STEM Education, as well as a laboratory elementary school and counseling center. Consistently recognized as NC's top producer of educators, the College maintained a large, active faculty workforce supporting high volume educator preparation pipelines.

The current Dean assumed leadership in 2023. At the time, the College of Education was comprised of 80 tenured and tenure track faculty. Given the number of faculty across programs, not including those who were on contracts, the need for an efficient and responsive organizational structure became paramount to meeting larger university initiatives. Thus, over the course of the academic year, the Team met two-three times monthly, with the first task to reduce the number of departments, reduce administrative costs, and create synergies between existing programs that could be combined. In one of our late Fall semester meetings, dialogue made apparent that this task was proving difficult given the history and relationships department chairs had with programs. In one of these sessions, the Team began using ChatGPT-4 to spur ideas and suggestions for programs that would be a good match if condensed and could lead to improved efficiency. For example, programs within each department were listed in ChatGPT-4 with the prompt to "pair programs in this list that would be the best fit and divide them into three-five departments." A series of suggestions were generated, with similar results across the Team. The Team then took time to evaluate results and discussed the pros and cons of each response taking into consideration pedagogical fit and the number of faculty in each department. Table 1 provides three examples of clusters used to generate discussion. These considerations were important since a reduction in administrative personnel was inevitable. The process continued for many sessions until several proposals were put together and presented to the Dean of the College. Afterwards, the Dean selected the most tenable and viable proposal and presented it for a faculty vote. As a result, AI assisted the leadership team in reducing the number of departments from six to four. Once the departments were selected, ChatGPT-4 was again used to generate ideas for department names that were shared among faculty who eventually voted for approval across individual departments. The result was the creation of the following departments that were finalized in Spring of 2025: (1) Educational Leadership and Foundations; (2) Elementary, Middle, and Secondary Education; (3) Interdisciplinary Professions; (4) Literacy Studies and Special Education (see Table 1).

Table 1

ChatGPT-4 examples edited by leadership team

Example 1 Departments	Programs	Total Faculty
1	K-12 School administration, Foundations, Research	23
2	Elementary education, Academically and intellectually gifted, Special Education	25
3	Literacy studies, History education, English education, Middle grades (Social Studies), Middle grades (English)	17
4	Science education, Math education, Middle grades (Science), Middle Grades (Math), Instructional technology, Business information technology in education	22
5	Counselor education, Adult education, Higher education, Library sciences	26
Example 2 Departments		
1	K-12 School administration, Higher education, Foundations, Research	27
2	Elementary education, Academically and intellectually gifted, Special education	25
3	Literacy studies, History education, English education, Science education, Math education, Middle grades	31
4	Counselor education, Adult education, Library sciences, Instructional technology, Business information technology in education	30
Example 3 Departments		
1	K-12 School administration, Higher education, Foundations, Research	27
2	Elementary education, Academically and intellectually gifted, Literacy studies	23
3	History education, English education, Science education, Math Education, Middle Grades, Business information technology in education	20
4	Counselor education, Special education,	24
5	Adult education, Library sciences, Instructional technology	19

Following the departmental consolidation, the leadership team pivoted to designing internal structures that provided essential operational support while introducing new, equitable leadership roles. During the Summer of 2025 a faculty task force was developed, and a three-day work meeting was established. Approximately 20 faculty and leadership team members joined this task force. Over the course of the meetings, discussions about the needs of each department were shared, as well as how each department functioned in handling those needs. What was immediately obvious was that each department had similar needs but varied in their current structure of leadership roles. For example, some departments had program coordinators who managed the curriculum for a degree area, while others had assessment coordinators. Each department operated in distinct ways to handle similar situations. Extensive notes for each meeting were taken. For instance, faculty shared their varied leadership roles and the duties that they specifically engaged in. At the end of the final task force meeting, these notes (i.e., data) were added to Gemini 1.5 Pro. Then, Gemini was prompted to “to summarize the notes, develop organization charts, develop examples of a leadership structure within departments, and to draft key roles/responsibilities for each leadership role based on the data that were uploaded.” Gemini assisted in creating a three-tiered support system that included an associate chair, program directors, and program specialists (Figure 1.1).

Figure 1.1

Three-tiered Departmental Leadership Support Structure

Department Chair
i. Associate Department Chair
ii. Program Directors
iii. Program Specialists

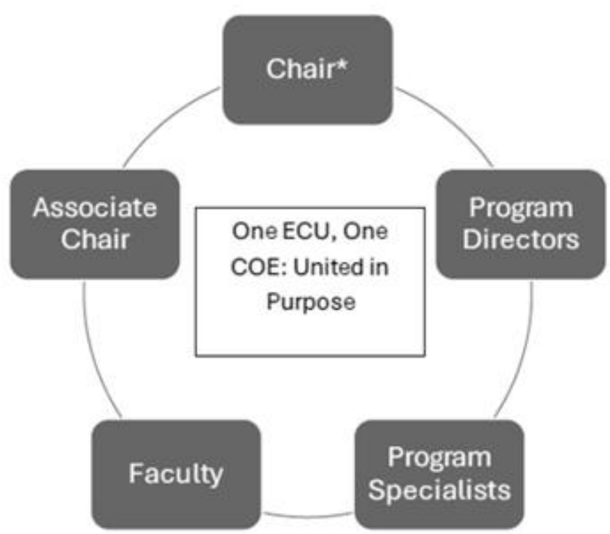

Figure 1. Community Leadership W/Primus (e.g., Greenleaf, 1977; Treadway et al., 2025)*

Legend. ECU: Eastern Carolina University; COE: College of Education

Figure 1.2 highlights the roles and parameters for the newly created position of Associate Chair. Results were shared with the leadership team and underwent several revisions based on feedback prior to implementation. One of these revisions ensured that the leadership model would be presented and grounded in the principles of servant (Greenleaf, 1977) and circular (Treadway et al., 2025) leadership. Blended together, these frameworks operate on the premise that the leader exists to serve the needs of the team (Greenleaf, 1977) while simultaneously engaging the voice of the community (e.g., the Department) to facilitate inclusive decision-making (Treadway, et al., 2025). In other words, the model portrayed a leader not *above* the others in relation to value and wisdom, but as one who holds a role of initiation (i.e., known as the Primus; Greenleaf, 1977). Thus, a leader is only *first* in a leadership team or community comprised of equals. Surprisingly, this refined process helped create a structure that was balanced and ensured equity across departmental leadership roles.

Figure 1.2

Associate Chair's Role Defined

General Role	Compensation	Length of Term
1. Curriculum and Course Management • Course Scheduling, course and section revisions based on enrollment numbers, hiring and credentialing part time instructors • Curriculum development • Catalog/Website Updates 2. Student Affairs • Oversight of advising • Student petition and waivers • Oversee recruitment and retention efforts 3. Faculty Support • Mentoring junior faculty	• 6500 Stipend or 5500 Stipend and 1k in Travel	• 3 year-Term

Lessons Learned and Implications

Through our approach, there were several lessons learned as well as implications. First, changing any managerial structure requires a level of emotional intelligence since department chairs and faculty have rooted connections to their programs that when challenged can result in resistance to change. In our case, resistance to change was handled by engaging in facilitated dialogue with faculty and leadership team members while also maintaining a level of transparency being careful to clearly articulate why changes needed to occur. A second lesson learned was that AI can serve as a legitimate neutral partner in strategic thinking to facilitate timely decision-making. Tools like ChatGPT-4 and Gemini 1.5 Pro were instrumental in generating ideas, modeling scenarios, and summarizing complex data. While AI was used to spur creativity and improve efficiencies, generated data were critically evaluated and refined by key players in the process to meet the contextualized needs of faculty. A third lesson learned was that collaborative efforts and faculty engagement were key throughout this restructuring. Regular meetings, faculty input, and collaborative dialogue helped to foster equity, smooth out transitions, and ensure consensus. Finally, AI was instrumental in processing large data sets and generating themes that helped to provide clarity, distill key needs, and align leadership roles that focused on departmental functions. We leveraged data-informed planning and AI to bridge the gap between complex organizational design and equitable leadership. This approach removed structural ambiguity, allowing us to implement an unbiased system with greater speed and clarity.

Conclusion

The above case illustrates how AI can serve as a powerful catalyst for organizational change in higher education. Faced with mounting external pressures such as declining enrollment, reduced funding, and shifting public sentiment, a leadership team leveraged AI tools not only to generate innovative solutions but also to facilitate collaborative decision-making on a short timeline. ChatGPT-4 and Gemini 1.5 Pro gave suggestions which ultimately led to a framework for the consolidation of departments and the reimagining of leadership roles, helping to create a more balanced and efficient structure. This process underscored the importance of emotional intelligence, transparent communication, and faculty engagement. Ultimately, AI proved to be a valuable strategic partner in navigating complex institutional challenges and in inspiring ideas for the design of sustainable departmental structures for the future.

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Journal of Higher Education Management, 41(1), 61-72 (ISSN 2640-7515).

Safeguarding Academic Integrity in the AI Era: A Case Study from Arizona College of Nursing

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Abstract

This case study explores the Arizona College of Nursing's (AZCN) proactive approach to maintaining academic integrity during artificial intelligence integration. Led by an AI Academic Integrity Task Force and strategic leadership, AZCN developed a policy balancing innovation and ethical responsibility. This paper presents a scalable five-component model: governance, policy clarity, capacity building, evaluation, and equity-by-design. Findings highlight faculty development, clear AI citation requirements, and communities of practice that promote responsible AI use while preserving professional judgment. The framework provides replicable strategies for nursing programs and higher education institutions committed to safeguarding academic integrity while advancing graduate preparation through technology.

Keywords: academic integrity, artificial intelligence in education, nursing education, AI policy development, faculty development, educational technology ethics.

Introduction: The Leadership Imperative in a New Technological Landscape

In professional programs where graduates are entrusted with human lives, the integration of artificial intelligence into higher education presents both extraordinary opportunities and complex ethical challenges. At AZCN, academic integrity is not only a matter of institutional policy but also of public trust. As students began to increasingly use generative AI tools, academic leadership prioritized establishing standards that preserve integrity without stifling innovation. The institution acted with urgency regarding implementing policy as underscored by scholarly concerns regarding the potential erosion of student learning outcomes if academic safeguards are not implemented (Sullivan et al., 2023). AZCN developed a five-component model encompassing governance, policy clarity, capacity building, evaluation, and equity-by-design. This model offers replicable strategies and solutions for higher education programs seeking to balance academic integrity and AI integration to prepare students for an AI-integrated workforce.

Methodology

The sections titled Formation of "The AI Academic Integrity Task Force" and "Defining Ethical Use Through Policy" were developed through a multi-stage qualitative process based on a thematic analysis of internal, non-public communications, including formal policy drafts, meeting minutes, and digital correspondence (e.g., Microsoft Teams chat threads and email exchanges). Initially, a generative AI model was utilized for a preliminary thematic analysis of these materials; however, to ensure institutional privacy and data integrity, the authors determined this output was not appropriate for the final manuscript. Consequently, all AI-generated material was discarded, and these sections were rebuilt through an independent, blind manual composition directly from the original source materials. For the final manuscript, across all sections, generative AI models (including Google Gemini [Google, 2025], Claude [Anthropic, 2025], and OpenAI [OpenAI, 2025]) were used as a collaborative tool for refining and enhancing the prose. The authors developed all core content through drafting and dictation and then transferred their initial drafts into the models, which refined text for clarity and flow.

A formal analytic coding process was applied to the primary documentation to validate the narrative and identify specific institutional friction points. Prior to this analysis, all raw data including Microsoft Teams transcripts, meeting minutes, and email exchanges underwent a rigorous manual de-identification process by utilizing Microsoft Copilot [Microsoft, 2025]. All names of students, faculty, and administrators, as well as specific institutional identifiers, were removed or replaced with generic descriptors to ensure complete institutional privacy and data integrity throughout the research process. This inductive process ensured that the findings were rigorously grounded in the primary documentation. During the coding process of the sanitized document, generative AI (Google Gemini [Google, 2025]) was utilized as a supportive tool for data organization and initial code-mapping; however, all final coding assignments and analytic memos were reviewed, validated, and finalized by the authors to ensure interpretive accuracy. To provide transparency, the authors developed a systematic coding framework (see Table 1), demonstrating the transition from raw data to the overarching themes. This sequential approach was crucial in allowing the authors to identify the internal consensus points, debates, and challenges that characterized the task force's work.

To assist with the initial drafting of the abstract, a generative AI model was prompted to generate an abstract based on the paper's content. The resulting AI-generated text was critically reviewed but ultimately discarded. The abstract was then rewritten entirely from scratch by the authors, incorporating some thematic ideas from the original AI output as guidance. All AI-generated revisions, across the entire manuscript, were rigorously reviewed, critically evaluated, and substantially revised by the authors to ensure accuracy, alignment with the paper's arguments, and the preservation of each author's unique voice and tone. Full responsibility for the final content rests solely with the authors.

Table 1:
Systematic Coding Framework and Institutional Friction Points

Final Theme	Primary Code	Description of Analytic Category	Example of Institutional Debate / “Difficult Conversations”
Institutional Governance	Stakeholder Representation	Determining the composition and scope of the AI Task Force	The Scope Debate: Discussions regarding whether the task force should focus strictly on student “cheating” or also include broader faculty innovation as it relates to AI
Technological Integrity	Detection Skepticism	Critical evaluation of AI-detection software and its limitations	The Reliability Tension: Significant debate occurred regarding the risk of “false positives” and whether to disable Turnitin features, citing precedents from other universities.
Policy Formation	Categorization of Misconduct	Defining the boundary between AI assistance and plagiarism	The Plagiarism Conflict: A deliberative debate on whether uncited AI use should be labeled “Plagiarism” or a new category of “Academic Misconduct”
Pedagogical Autonomy	Granularity vs. Judgment	Balancing strict thresholds with professional educator discretion	The Threshold debate: The task force initially recommended a strict % threshold for investigations; however, leadership ultimately shifted to a principle-based policy favoring faculty autonomy.
Capacity Building	Ethical Disclosure	Establishing norms for how both students and faculty disclose AI use	The Disclosure Dilemma: Conversation over whether faculty should disclose AI use for “simple re-wording” of course content vs. providing student feedback

Formation of the AI Academic Integrity Task Force

As AI integration into higher education became increasingly prevalent and the need for a deliberative course of action became apparent, AZCN leadership acted promptly to invite representatives to participate in an AI Academic Integrity Task Force. The task force was established in June of 2023, with meetings beginning the following month. Two of the paper's authors along with a mix of faculty, deans, and administrators participated extensively in this task force with the objective of recommending college-wide standards for AI use by both students and faculty. The task force set out to address a series of initial objectives and questions, including:

- What types of AI-generated content would be acceptable from students for assignments, and what type of content would be acceptable from faculty and staff to create course content?
- How should AI-generated content be properly cited in assignments and course materials?

- When using plagiarism checkers in assignments, what percentage of cited vs. uncited AI content would be acceptable for students to use?
- What definitions for plagiarism and for various types of AI, including predictive AI, generative AI (e.g., ChatGPT, Google Gemini, Grammarly), and machine learning, should be used to inform policy development?

While these initial questions formed the basis for some areas of concern, the task force remained open to exploring any further concerns that could arise.

The task force worked promptly to gain further knowledge of how AI could best be integrated into the student learning experience. As part of this effort, leadership initiated a meeting with representatives from Grammarly. The task force also attended a Grammarly-sponsored "Fireside Chat" on June 18, 2023, titled "Generative AI in Education" with learning technology expert Brian K. Smith, The Honorable David S. Nelson Chair and Associate Dean at Boston College (Smith & Collins, 2023). The presenter detailed how higher education institutions can ethically expose students to AI in the classroom to teach them responsible use. Of note was a link provided in the webinar chat to sample policies and procedures that other colleges were adopting at the time. On July 25, 2023, Grammarly was also invited to demonstrate its software. Although AZCN leadership decided not to proceed with full Grammarly integration, task force members were invited to sign up for a free Grammarly account which included a beta version of their generative AI product, Grammarly Go. This provided a unique opportunity for members to begin using Grammarly generative AI tools.

As the task force continued to collaborate, a primary driver of the reliability tension emerged when one of the paper's authors raised key concerns regarding the complexities and potential limitations of AI detection tools. In support of these concerns, the author highlighted OpenAI's own recent admission that its detection software couldn't reliably distinguish between human and AI-generated content (Edwards, 2023). A deep concern was shared over potential "false accusations" and the long-term reputational risk to the College. This concern was further supported by highlighting examples from the University of Michigan and the University of Pittsburgh, which had both decided to opt out of the Turnitin AI detection feature (EdScoop Staff, 2023; University of Pittsburgh, n.d.). The University of Pittsburgh, in particular, states on their website:

> Based on our professional judgment, the Teaching Center has concluded that current AI detection software is not yet reliable enough to be deployed without a substantial risk of false positives and the consequential issues such accusations imply for both students and faculty. Use of the detection tool at this time is simply not supported by the data and does not represent a teaching practice that we can endorse or support. Therefore, the Teaching Center has disabled the AI-detection tool in Turnitin. **(**University of Pittsburgh, n.d.).

Another member pushed back, insisting that throwing the tools out entirely wasn't the answer either and that the institution planned to keep these detectors to help hold students accountable. This member emphasized that the institution has a unique focus on healthcare and medicine which requires stricter accountability compared with other colleges. The reliability of Turnitin's AI detection was further questioned by highlighting its detection capabilities as noted in its FAQ section, particularly for writing samples under 20% AI detection or fewer than 300 words because of a higher incidence of false positives (Turnitin, n.d.). A key takeaway was also discovered in a CNBC television interview with Turnitin's CEO, Chris Caren, in which he expressed that while some AI involvement is acceptable, extensive AI generation (e.g., 80% or more) in core sections like conclusions and critical thinking would typically constitute misconduct (CNBC Television, 2023). Caren suggested a high threshold for how much AI generation could be considered misconduct. One committee member further noted the emergence of “bypass” tools such as Phrasly.ai that is specifically designed to bypass Turnitin, noting, “When AI is written to detect AI, more AI is written to bypass AI detection.” This discourse about technological promise and practical reliability was a primary driver for the task force’s concerns about strict thresholds and automated detection.

Understanding the need to address these concerns, leadership continued to seek out the advice of additional perspectives, including consulting with other university educational technology and online learning professionals. AZCN leadership specifically reached out to a Turnitin representative for statistics and testimonials from other schools utilizing Turnitin and to course building professionals through LinkedIn and eLearning sites. After gathering and discussing this information, the group decided to continue supporting the use of AI detectors to help hold students accountable. The group emphasized that the institution would need to train and educate instructors on proper use and interpretation of the AI detection tool to address and engage with students who are flagged for AI usage. The task force agreed that the use of AI detection tools should support, and not replace, educator judgment. Having agreed to continue using AI detection tools, the task force planned to establish clear guidelines for AI use and to recommend a dedicated and comprehensive policy that would balance academic integrity with the responsible use of AI.

Defining Ethical Use Through Policy: From Recommendations to Implementation

The initial guidelines and recommendations developed in an internal document by the task force provided a framework and a reference for AZCN leadership to consider as they crafted the official policy that the school would eventually adopt. Within the document, the task force initially defined several important terms such as AI, Generative AI, Large Language models, and plagiarism. Interestingly, the word *plagiarism* itself became a point of concern as the group debated whether the use of uncited AI would be considered a form of plagiarism or a separate form of academic misconduct. One member suggested that the student handbook already has a definition of plagiarism in it and that perhaps the group should reference it and add it into the document. The plagiarism conflict was further expressed when one of the authors of this paper shared a more nuanced consideration with a link from Originality.ai within the task force’s Microsoft Teams channel. This source provided the following insight:

> Checking for plagiarism is widely understood, it has been done online for decades. It is a very clear process where if a section of text is copied from somewhere else then it is plagiarized. However, checking and interpreting the results of AI detection is a much more nuanced activity. The results are not as “binary” as plagiarism detection meaning there is more room for interpretation” (Originality.ai, 2023).

After seeing this commentary, one committee member noted, “I guess we’re spot on with our thinking.” This insight highlighted that AI-generated results require significantly more human oversight and room for interpretation. After agreeing upon a definition of plagiarism and concluding that uncited AI generation should be included as a form of plagiarism, the task force advised that if generative AI is used and cited properly, it should not be considered plagiarism and recommended that any verbiage suggesting otherwise be removed from current policy.

The task force further outlined recommendations for the appropriate use of generative AI by both faculty and students alike. For example, it was recommended that if a faculty member were to use generative AI to help provide feedback to students on assignments or discussion boards, faculty would be advised to disclose the use of AI in the feedback. However, if the faculty were to use generative AI for simple re-wording for assignments, discussion prompts, better communication, or something similar, the group recommended that there would be no need to cite the source as the original idea would be coming from the faculty member. Disclaimers were proposed for both faculty and students, emphasizing the potential for generative AI applications to have inaccuracies, making it crucial for human review and for the faculty and students to take ownership and responsibility to ensure the accuracy of the generative content created.

Recognizing the utmost importance for academic integrity in relation to the use of AI by students, it was advised that faculty address the use of AI at the start of each semester/course. The group proposed sample verbiage that faculty could use within an announcement or added to other course materials such as the syllabus or within an introductory PowerPoint. This group recommended that students be responsible stewards of their use of AI by validating the content and citing the source. The group also stressed that generative AI would not be considered a scholarly resource. The group further recommended that all students use APA format citations when utilizing generative AI to assist in creating authentic and original material and that this APA requirement be applied to discussion board responses, writing assignments, essay prompts in online tests, or any other written response required in a course. The task force proposed acceptable examples of citations for generative AI placed in proper APA format and provided an example for both a reference entry and an in-text citation.

The task force further made recommendations for how faculty should properly engage with Turnitin and subsequently with students. Acknowledging that Turnitin does not treat their AI indicator score in the same way that they do their Similarity score, the group advised that these two scores should be evaluated separately. To deal with standard plagiarism not involving AI, the group recommended that if a similarity score exceeded 30%, faculty would need to investigate further and outlined a process for documenting their findings. The task force further stressed that faculty would need to understand that the use of generative AI would not automatically mean academic dishonesty and recommended that if an AI writing indicator percentage of 40% or higher was detected by Turnitin, faculty would need to look at the document and determine if a meeting was necessary. The group recommended a specific process for the faculty to consider prior to contacting the student and outlined additional steps and processes for investigating and documenting any meetings and academic dishonesty concerns with students. Finally, the group recommended that faculty be directed to a number of resources from Turnitin, including two PDF resources titled "Discussion Starters for Tough Conversations about AI" (n.d.) and "Approaching a Student Regarding Potential AI Misuse" (n.d.) and two YouTube videos titled "Understanding False Positives Within Turnitin's AI

Writing Detection Capabilities" (2023) and "Understanding the False Positive Rate for Sentences Within Our AI Writing Detection" (2023).

Following the detailed and comprehensive recommendations made by the task force, leadership took the critical step of developing a clear and condensed academic integrity policy that addresses artificial intelligence by embracing its ethical application. Institutional leadership made some key strategic decisions and took a more streamlined and principle-driven approach as opposed to adopting all the procedural and intricate recommendations made by the task force. For example, the task force's engagement in a threshold debate led to specific recommendations detailing specific Turnitin scores (e.g., 30% for similarity, 40% for the AI indicator score), detailed steps for investigating academic misconduct, and specific protocols for meeting with students. Leadership ultimately opted for an approach that favored faculty judgment over specific rules and numerical triggers. By taking this action, the policy extends beyond prohibition or strict granular rules and procedures. While still embracing core elements of the task force's advisement, the policy establishes a clear definition for AI plagiarism, outlines clear guidance for citations, establishes transparent guidelines for violations of scholastic misconduct, and allows faculty the autonomy and freedom to exercise their best judgment.

To clarify AZCN's interpretation of plagiarism, the final policy explicitly states that "a paper created by Artificial Intelligence (AI), such as ChatGPT, Sudowrite, etc. without proper citation" is an example of plagiarism (Arizona College of Nursing, 2025). One of the most important requirements that was included in the policy elaborates that "the use of AI sources must be properly cited and follow established guidelines. All students must use APA format citations when utilizing generative AI" (Arizona College of Nursing, 2025). Another key step that leadership took was ensuring that additional guidance and a reference back to the Arizona College of Nursing Academic Catalog was added to every syllabus in every course. The policy further allows faculty to rely on the detailed guidance that is provided from Turnitin on how to interpret and navigate the complexities of the similarity and AI indicator score without dictating a strict number that would trigger an investigation or constitute a potential academic dishonesty violation. The policy makes clear that the institution is committed to academic integrity by holding students accountable for independent thought and proper citation and allowing faculty to use their own judgment when assessing student writing and assignments. By supporting innovation while still upholding the key principles of academic integrity, this approach aligns with emerging recommendations for AI-integrity frameworks, particularly within health-related disciplines where the stakes for academic honesty and professional conduct are exceedingly high (Unbound Medicine, 2025).

Empowering Faculty to Lead Responsibly

In higher education's rapidly evolving technological landscape, faculty are not merely course deliverers; they are the frontline stewards of academic integrity, pedagogical quality, and professional judgment. At the AZCN, empowering faculty to lead responsibly in an AI era requires deliberate, future-focused action. Rather than allowing AI to supplant faculty authority, institutions should enable educators to use AI as a pedagogical partner—one that enhances learning while preserving human oversight, professional ethics, and academic standards.

Effective faculty leadership begins with shared AI literacy, which requires an understanding of what AI can and cannot do, the ethical risks it poses, and the pedagogical affordances it offers (American College of Education [ACE], 2024). AZCN provides structured learning opportunities that help faculty evaluate AI outputs critically; teach students how to use AI responsibly; and design learning experiences that require higher-order cognitive skills that AI cannot replicate.

To enable responsible faculty leadership, AZCN embeds clear policies and structural supports into institutional strategy. Policy measures require the disclosure of AI use, define acceptable practices, and delineate processes for academic integrity incidents. Coupled with ongoing professional development and opportunities for cross-faculty collaboration, these policies provide the infrastructure necessary for sustained ethical AI integration (Times of India, 2024).

Faculty members serve as guardians of institutional credibility and student competence. To strengthen this stewardship, AZCN has invested in targeted professional development that equips faculty for AI-enhanced teaching and assessment. Training focuses on responsible use and disclosure practices, proficiency with AI-detection tools, assessment redesign to reduce opportunities for misuse, and integration of digital ethics into course design. A consistent curricular framework provides alignment and quality assurance while permitting faculty to exercise creativity within set parameters. Such capacity-building enables faculty to make informed decisions about technology adoption and to ensure AI functions as a complement and not a replacement to professional judgment.

Empowerment also depends on collaborative structures. AZCN has created faculty communities of practice, interdisciplinary working groups, and mentoring cohorts where educators can explore AI tools, critique one another's approaches, and disseminate discipline-specific best practices (AACSB, 2024). These safe, low-stakes environments for experimentation allow faculty to iterate on AI use and to share what succeeds or fails. An "Experiment, Share, and Learn" approach fosters improvement and collective learning (Digital Education Council, 2024). Regular reflective practice, supported by peer feedback, helps faculty refine AI-mediated pedagogy so that technology enhances and does not eclipse learning objectives. By integrating AI into lesson planning and dynamic case scenarios that remain faithful to curricular standards, faculty can personalize learning experiences without sacrificing consistency across the program. This approach allows AZCN to leverage AI in concert with a standardized curriculum to foster effective collaboration.

A Scalable Model for Ethical AI Integration

AZCN's approach can be generalized into a practical model that other professional programs can adapt to mission, size, and regulatory context. The model rests on five mutually reinforcing components: governance, policy clarity, capacity building, evaluation, and equity-by-design. Each component aligns with established guidance so that integrity protections scale with innovation rather than stifle it (National Institute of Standards and Technology [NIST], 2023, 2024; United Nations Educational, Scientific and Cultural Organization [UNESCO], 2023; American Association of Colleges of Nursing [AACN], 2021).

Governance provides direction and accountability across the AI lifecycle. Institutions should charter a cross-functional body with authority to approve use cases, assign roles, and manage risk from development through deployment. This governance structure requires representation from academic affairs, information technology, legal counsel, student services, and discipline-specific faculty to ensure comprehensive oversight. NIST's AI Risk Management Framework offers a structure to map contexts of use, measure risks and benefits, manage controls, and govern operations, helping leaders translate institutional values into actionable decisions and documentation (NIST, 2023, 2024). The governance body should establish regular review cycles, maintain incident response protocols, and ensure alignment between AI policies and accreditation standards.

Policy clarity defines responsible use for students and faculty while fostering innovation within appropriate boundaries. Transferable elements include explicit definitions of permitted and prohibited uses, standardized citation norms for AI assistance, detailed expectations for documenting prompts and outputs, and graduated consequences for policy violations. In nursing education, alignment with the AACN Essentials ensures that integrity standards strengthen competencies in ethics, informatics, communication, and clinical judgment rather than compete with them (AACN, 2021). Policies must address discipline-specific concerns such as patient privacy, clinical reasoning development, and professional identity formation while providing concrete examples and scenarios that help learners understand acceptable boundaries.

Capacity building equips people to apply policy in authentic educational tasks. Faculty development should cover assessment, redesign methodologies, effective use of detection tools, verification strategies for AI outputs, and case-based judgment exercises that mirror real-world scenarios. Student orientation should teach proper attribution techniques, systematic recordkeeping of AI assistance, and structured reflection on how AI influences reasoning processes. UNESCO's guidance emphasizes teacher preparation and learner agency as prerequisites for safe and effective adoption (UNESCO, 2023). These initiatives must be ongoing rather than one-time events, adapting to evolving technologies and emerging best practices.

Evaluation makes the model self-correct through systematic monitoring and improvement processes. Implementation-science frameworks help teams identify determinants of success and monitor outcomes at institutional scale. Consolidated Framework for Implementation Research (CFIR) 2.0 supports diagnosis of contextual factors such as leadership engagement, available resources, and equity considerations that influence adoption success (Damschroder et al., 2022). The RE-AIM framework (Reach, Effectiveness, Adoption, Implementation, and Maintenance) focuses attention on these dimensions, promoting continuous improvement rather than one-time compliance (Glasgow et al., 2019). Evaluation strategies should capture both intended and unintended consequences, measuring policy adherence, learning outcomes, faculty confidence, and student preparedness for professional practice.

Equity-by-design ensures the model works across campuses and learner populations. Programs should plan for multilingual resources, accessibility accommodations, and infrastructure constraints, and then tie those supports to discipline-specific competencies in ethics and informatics. This model includes addressing digital divides that may disadvantage certain student populations and ensuring that AI tools enhance rather than replace essential human skills. When the five components operate together, institutions preserve academic integrity, build professional competence, and scale responsibly across diverse contexts (UNESCO, 2023; AACN, 2021).

Conclusion: Leading with Integrity in the Age of Artificial Intelligence

Academic integrity in the AI era must be viewed as an evolving responsibility of leadership. AZCN's experience demonstrates how ethically grounded leadership can safeguard core values while embracing technological advancement. Empowering faculty to lead responsibly in the AI era is a multi-dimensional effort that requires building AI literacy, aligning institutional policy and resources, cultivating collaborative communities of practice, supporting reflective experimentation, and centering ethics. By treating AI as a facilitator, rather than a substitute, and by investing in faculty capacity and collective inquiry, AZCN harnesses technological innovation while safeguarding the professional judgment and integrity at the heart of nursing education.

AZCN's experience, centered on proactive leadership, policy clarity, faculty development, and student engagement, offers a replicable framework for institutions to manage AI technological change responsibly and ethically. This approach shows that ethical AI integration is not a single policy choice but a leadership practice that coordinates governance, policy clarity, capacity building, evaluation, and equity. The result is a learning environment that protects academic integrity while preparing graduates to use AI judiciously in complex, real-world settings. For nursing programs, the AACN Essentials anchor this work by linking integrity to patient safety and professional identity formation (AACN, 2021). For institutions broadly, NIST's framework provides a practical scaffolding for oversight, and UNESCO's guidance centers human rights, transparency, and inclusion (NIST, 2023, 2024; UNESCO, 2023).

Leaders can act now in three strategic ways that build institutional capacity while maintaining academic standards. First, leaders can formalize cross-functional governance with clear authority to vet use cases, document decisions, and adjust controls as evidence accumulates from implementation experiences. This governance approach moves beyond traditional committee structures to create dynamic oversight mechanisms that can respond to rapidly evolving technological capabilities. Second, leaders can invest in faculty development that pairs assessment redesign with integrity scenarios, explicit student guidance on attribution, and verification routines for AI outputs. These development programs must be ongoing rather than one-time training events, recognizing that AI capabilities and best practices continue to evolve rapidly. Third, leaders can evaluate at scale by using CFIR to understand context and RE-AIM to track outcomes that matter to learners, faculty, accreditors, and the public (Damschroder et al., 2022; Glasgow et al., 2019).

These priorities create a durable feedback loop that supports continuous improvement rather than static compliance. Governance sets expectations and accountability mechanisms, and capacity building enables responsible practice by ensuring stakeholders possess necessary knowledge and skills. Additionally, evaluation drives evidence-based improvement by identifying successful strategies, and equity safeguards access and fairness across diverse learner populations. Institutions that lead in this coordinated way will sustain public trust while graduating professionals who can harness AI responsibly and ethically. The framework developed at AZCN offers a practical pathway forward, but success ultimately depends on leaders' sustained commitment to placing ethical considerations at the center of technological innovation in education.

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Journal of Higher Education Management, 41(1), 73-85 (ISSN 2640-7515).

From Silos to Synergy: Statewide Collaboration as a Model for Ethical and Scalable AI Integration

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Abstract

Higher education faces ongoing challenges with generative artificial intelligence (GenAI) in teaching and learning. Institutions' efforts are frequently siloed, hindering coherent, ethical, and scalable AI integration. This article presents a statewide, cross-institutional model that leverages Centers for Teaching and Learning (CTLs) to navigate pedagogical change. Through a three-phase process—shared inquiry, resource development, and strategic dissemination—we enabled faculty, staff, and students to become local experts on GenAI so that necessary conversations about AI integration could transcend institutional boundaries. We offer a replicable model of cross-institutional collaboration as one powerful way to address the complex challenges facing higher education today.

Keywords: Generative Artificial Intelligence, Higher Education, Cross-Institutional Partnerships, Teaching and Learning

Introduction

By academic year 2023–2024, the need to understand and respond to generative AI (GenAI) in higher education had become urgent. Instructors were being asked to make rapid decisions about syllabus policies, assignment design, and learning outcomes in the face of powerful new tools, while institutions struggled to respond to this pedagogical upheaval. How could they move from ad hoc experimentation and piecemeal adoption of tools to coordinated, ethical, and scalable integration in ways that reflect the practical realities of diverse teaching and learning contexts?

In this article, we propose one possible approach: a statewide, cross-institutional model that leverages Centers for Teaching and Learning (CTLs) to foster a holistic response to pedagogical change and enable innovation at scale. Through a three-stage process of shared inquiry, resource development, and strategic dissemination, our CTLs served not just as sites for pedagogical skill development, but as incubators for distributed leadership in AI-informed teaching—fostering instructor agency, peer learning, and evidence-informed resource creation. This initiative is the product of years of intentional collaboration among educational developers, researchers, instructors, and administrators across Virginia, many of whom had already worked together on educational development efforts focused on equity, transparency, and student success. These efforts emphasized inquiry-driven, evidence-informed, and equity-centered approaches to teaching improvement, principles that would prove essential as GenAI technologies began to disrupt conventional academic practices. These preexisting networks, including the Virginia Educational Development Collaborative (VEDC) and the Scholarship of Teaching and Learning Collaboratory (SoTL-C), created the foundation for our rapid and research-informed response to GenAI.

Rather than rush to implement isolated workshops or compliance-oriented policies, three educational developers launched a statewide initiative focused on understanding how GenAI was already affecting teaching and learning, and how instructors and students were navigating these changes in real time. This inquiry-first model allowed faculty, staff, and graduate students to explore their own questions through research teams focused on key challenges: accessibility, feedback, onboarding, assessment, assignment design, and more. These research projects were not separate from the development of practical resources; rather, they were catalysts. Findings from these studies directly informed the creation of open educational materials, faculty workshops, and instructional strategies that could be adapted across institutions. As a result, instructors were not simply passive recipients of professional development; they were active contributors to it.

By drawing on an existing collaborative infrastructure, this initiative was able to move quickly and strategically, with CTLs playing a central role in convening teams, mentoring researchers, and translating findings into action. The result is a replicable model for how institutions—or groups of institutions—can respond to disruptive technologies not with reactive policy, but with thoughtful, research-informed, and collectively shaped innovation.

Literature Review

The rapid emergence of GenAI presents a new kind of disruption for higher education, one that is not only technological, but also deeply pedagogical, ethical, and relational. Educational developers play a pivotal role in shaping institutional responses to teaching-related change, often acting as bridges between faculty, administrators, and broader educational trends and pressures (Amundsen & Wilson, 2012). In contexts of disruption, whether the shift to online learning in 2020 or the current wave of GenAI, CTLs often mediate competing priorities and support pedagogical innovation at scale. CTLs increasingly serve as change agents within higher education institutions, bridging faculty experience, student needs, and institutional goals. In turn, educational developers increasingly engage in work that is relational, contextual, and sensitive to institutional culture (Gibbs, 2013; Mårtensson & Roxå, 2021).

Institutional culture is not simply a backdrop for AI integration efforts: it actively shapes how instructors engage with new pedagogical tools, whether they feel supported in innovation and how their decisions are interpreted by peers and leadership (Lewis & Steinert, 2020; Meadows et al., 2024). Teaching-related decisions, including whether and how to adopt GenAI, are often shaped by "microcultures" within departments and peer groups (Roxå & Mårtensson, 2015). These localized norms reinforce the sense that faculty operate in largely autonomous silos; however, evidence shows faculty professional development is most impactful when it occurs in relational spaces, such as the cross-institutional and interdisciplinary research group that is the focus of this article, that promote peer dialogue, support, and access to diverse perspectives and resources (Barry, 2023; Bayraktar, 2024; Bayraktar et al., 2024; Xie & Rice, 2021). These structures are particularly important for supporting inclusive participation across disciplines and appointment types (Benbow et al., 2021; Castillo-Montoya et al., 2023).

Collaboration across institutions to solve institutional, pedagogical, and research challenges is not new. It is also not without challenges. Colleges and universities are not structured to work together, even within state systems (Duffield et al., 2012). Each institution operates based on its own mission, with leaders focused on creating a distinct and recognizable identity. Because of the current state of higher education, particularly in the U.S., institutions are forced to compete with one another for funding, enrollment, and research grants among other resources. By both tradition and practice, most institutions function autonomously. Additionally, in most institutions, faculty tend to operate with a high degree of autonomy, often in disciplinary or departmental silos that limit cross-pollination of pedagogical ideas and innovations. While this independence can support disciplinary depth and instructional flexibility, it can also hinder coordinated responses to emerging challenges. Without mechanisms for structured dialogue or shared professional learning, instructional decision-making around new technologies can remain fragmented and shaped by local norms rather than institutional values. Educational developers and CTLs therefore play a vital role in creating collaborative infrastructures that disrupt isolation and foster distributed leadership. Our work extends prior research on the impacts of institutional culture on professional learning by showing how collaborative, cross-institutional structures can amplify local efforts and counteract the siloing effects of institutional microcultures (Beach et al., 2023; Mårtensson & Roxå, 2021; Steinert et al., 2024).

Our Approach: The Statewide Collaboration

The creation of our original cross-institutional collaboration is explained elsewhere (see Lukes et al., 2023) and the impacts of the original collaboration on institutional culture related to the Scholarship of Teaching and Learning (SoTL) have been theorized and demonstrated (Abbot et al., 2024). Here, we focus on how we leveraged our existing collaborative network to address the challenges of GenAI in teaching and learning.

Phase 1: Shared Inquiry through Cross-Institutional Research Teams

Team Formation

We, the three educational developers leading this initiative as co-principal investigators (PIs), have worked together since 2021 on various Scholarship of Teaching and Learning (SoTL) initiatives. We all have positive prior experiences with cross-institutional collaboration and appreciate the opportunity to build community with colleagues at other institutions.

In Summer 2023, we saw the need to bring together faculty, staff, and graduate students to study the impacts of GenAI on teaching and learning. From the start, our goal was to be inclusive of instructors from across the state and to represent the range of institutions, roles, disciplines, and

contexts in which educators find themselves. We issued an open call through our CTL newsletters and the VEDC for potential collaborators. Over 90 instructors completed our initial interest survey, and 53 joined our two virtual information sessions. Instructors were invited to sign up for projects in the domains of student perceptions of GenAI, student (mis)use of GenAI, student support, and course design/facilitation; 45 signed on, with 17 volunteering to be a team lead or co-lead.
We initially formed eight project teams with 26 leads, co-leads, and team members, and now, two years later, have seven project teams with 28 collaborators representing 6 institutions and a range of professional roles and disciplines (see Table 1). For most of the research team members, this was their first experience collaborating on SoTL with other institutions.

Table 1
Collaborator Demographics

		Number of Collaborators *n* = 28
Professional Role	Assistant Professor	7
	Associate Professor	5
	Professor	4
	Lecturer	3
	Adjunct	1
	Postdoc	1
	Graduate Student	2
	Staff	5
Discipline	Humanities (English, Focused Inquiry, French)	4
	Social Sciences (Communication Studies, Leadership, Psychology)	4
	STEM (Biology, Data Science, Engineering)	5
	Professional (e.g., Business, Commerce, Education, Law, Nursing)	10
	Library (IT Director for Health Sciences, English, Multimedia Teaching and Learning, Teaching and Instructional Design)	4
	Learning Design and Technology	1

To collect data on the experience of these research team members, a survey was administered to team members, and team leads were asked to volunteer for a focus group or interview about their experiences. The survey and focus groups/interviews were IRB-approved and carried out by one PI and team member assigned to project assessment. The survey was sent to 27 research team members, 14 of whom identified as leads/co-leads. Twenty participants completed all questions, and four participated in focus groups/interviews. In the survey, participants noted a variety of motivations for participating in this project (see Table 2). Overall, they were highly motivated by the project's focus on AI, and it was very important to them that the project be collaborative and involve multiple institutions. They also felt it important that the project benefited both their teaching and scholarship.

Table 2
Median Importance Ratings for Motivations to Participate in MegaSoTL - AI

	Team Leads *n* = 9	**Team Members** *n* = 10
The focus was on artificial intelligence (AI).	5	4
The project was collaborative.	4	4
The project involved multiple institutions.	4	4
The project will positively benefit my teaching.	3	4
The project will benefit me professionally.	3	4

Note. Scale from Not at all important (1) to Extremely important (5).

Team Inquiry

The team projects examine a variety of research topics focused on AI in teaching and learning in higher education, including:

- **AI as a Support for Students with Disabilities.** This project explores whether and how GenAI might support students with disabilities or learning differences.
- **Onboarding: What Do Students Need to Know Before Being Invited to Use AI?** This project develops and evaluates onboarding activities designed to increase student understanding of and comfort with GenAI.
- **OER for Teaching with AI.** This project develops and evaluates an open educational resource (OER) designed to aid educators in developing AI literacy.
- **Measuring and Grading Learning Done with AI.** This project examines how to measure and grade student learning done in collaboration with GenAI.
- **AI-Incorporating Learning in the Writing Classroom.** This project develops a framework for how instructors are experiencing and adapting to the impacts of GenAI on college writing.
- **Instructor Responses to Generative AI in Classroom Assessment.** This project explores educator attitudes towards GenAI and the assessment strategies they have adopted in response to their concerns.
- **The Potential of AI for Personalized and Constructive Feedback.** This project explores the potential of GenAI to provide personalized and constructive feedback to students on their written work as part of the revision process.

From August through December 2023, the PIs liaised with the teams, attending regular meetings to help refine research questions, develop methods, and prepare institutional review board (IRB) documents. The PIs also met weekly to keep each other updated on the progress made by each team and develop the IRB protocols necessary to carry out cross-institutional research. In January 2024, we submitted IRB protocols to cover student- and instructor-focused projects. One institution served as lead, with reliance agreements for all other institutions. Data collection began in Spring 2024 and has continued since. As part of the data collection activities, we planned to formally evaluate the project through surveys, interviews, and focus groups with the project team members. In the mid-year feedback survey, team members were asked about the project overall and specifically about their roles, responsibilities, and how well supported they felt in these roles (see Table 3).

Table 3

Median Support and Understanding Agreement Ratings

	Team Leads ***n* = 9**	**Team Members** ***n* = 10**
I received adequate support from the project PIs.	6	.
I received adequate support from my team lead.	.	6
I had a clear sense of my roles and responsibilities as a team lead.	5	.
I had a clear sense of my roles and responsibilities in my team's project.	5	5.5
I understand how each individual research project fit into the Mega-SoTL AI project.	5	5.5

Note. Scale from Strongly Disagree (1) to Strongly Agree (7).

Overall, the team *leads* felt supported by the PIs; seventy-eight (78%) agreed or strongly agreed that they received adequate support from the project PIs, with comments like:

> [The PI partnered with our team] has been consistently attending our team [meetings] and [is] very invested in our project; I really appreciate that, her taking time, but also we can check in with her in terms of getting support for project management, or checking on progress related to the IRB... so we always feel like we have someone...connected to us very closely that we can check in [with] and seek feedback whenever we need."

The remaining two team leads were neutral or somewhat agreed. Most team *members* agreed or strongly agreed that they were adequately supported by their team lead (n = 8, 80%).

The data also showed that collaborators may have benefited from a clearer sense of their roles and responsibilities. Of the 9 team leads, just 4 (44%) agreed or strongly agreed that they had a clear sense of roles and responsibilities as a team lead, their role in the team's project, and the way in which each individual research project fits into the MegaSoTL-AI project. Of the 10 team members, just 5 (50%) agreed or strongly agreed that they had a clear sense of their roles and responsibilities. When asked for suggestions for improvement, their feedback focused on greater transparency within and across teams: "...set clear expectations and requirements for participating in the project. Provide more guidance for individual team leaders regarding research design and project management" and "...hav[e] a couple more of those Zooms were [sic] all of the teams came together and shared updates on where their projects were at would be helpful." In the lessons learned section below, we outline how we have worked to improve our processes to meet this need for greater clarity of roles and responsibilities.

Participation in this shared inquiry has had positive impacts on collaborators (see Table 4) – from learning more about AI to developing collaboration and leadership skills and expanding professional networks. While they are not yet reporting specific benefits of the work directly in their teaching, we expect these benefits to come.

Table 4
Median Agreement Ratings for Impact of MegaSoTL - AI

	Team Leads ***n*** **= 9**	**Team Members** ***n*** **= 10**
I learned more about AI	5	5
I developed collaboration skills	6	6
I developed leadership skills	6	4
I expanded my professional network	7	6
I improved my teaching	5.5	4.5

Note. Scale from Strongly Disagree (1) to Strongly Agree (7).

Phase 2: Resource Development

It was essential to us that the research findings be used to inform resource development that would support educators across the state and beyond. Thus, following the strategic inquiry phase, several asynchronous resources were developed for instructor and researcher use. These resources include, to date, an annotated bibliography, an open educational resource (OER), and collections of resources hosted on Teaching Hub (https://teaching.virginia.edu), a website designed to crowdsource the best pedagogical resources for educational developers and higher education instructors.

The annotated bibliography compiles relevant resources and literature on GenAI in teaching and learning; it can be used by instructors and researchers alike to inform their teaching and scholarship. The OER, *Fostering AI Literacy: A Guide for Educators in Higher Education* (https://pressbooks.library.virginia.edu/ai-literacy), is designed to help instructors develop AI literacy and make intentional, informed course design decisions that cultivate students' AI literacy. Teaching Hub hosts collections of resources composed by the research teams, ranging from activities instructors can use to onboard students to GenAI in the classroom to information about how to use GenAI to support students with disabilities. These resource collections continue to evolve alongside our shared inquiry. Most importantly, every one of these resources is available to instructors beyond our institutions.

To enable this resource development and dissemination, we found it necessary to secure external funding for the project. In October 2023, the State Council of Higher Education for Virginia (SCHEV) released a call for proposals through the Fund for Excellence in Innovation (FFEI) program, focused on integrating AI in accordance with the governor's guidelines for AI integration in education. In early 2024, we were awarded a $93,000 grant that has allowed us to provide additional support to the research teams and to develop and disseminate both asynchronous and synchronous resources for instructors.

Phase 3: Strategic Dissemination

We are now at the phase of strategically disseminating our work from Phases 1 and 2 in the form of publications, presentations, and workshops. Currently, we offer a workshop on developing and communicating syllabus policies on the ethical use of GenAI. We tracked engagement at our first three offerings: a regional conference focused on higher education pedagogy, a statewide webinar, and an invited workshop as part of an institution's faculty development activities. For the pedagogy conference, 19 participants registered, representing two 2-year public institutions, five 4-year private institutions, eleven 4-year public institutions, and one (1) unknown. For the statewide webinar, 540 participants registered. Just under half (n = 224) were from four-year public institutions; the other half were from community colleges (n = 211), four-year private institutions (n = 78) and other types of institutions including professional schools, K-12, and government organizations. The invited workshop included over 90 participants from a small public research university.

In addition to this workshop, we have facilitated thirteen other workshops and presentations at research and teaching conferences, summits, and institutional professional development symposia. Six additional presentations have been submitted; four have been accepted, and two are under review. We have thus far submitted four papers for publication with one being accepted and published (Bayraktar et al., 2025) and two in-press. Finally, we most recently co-convened a symposium on AI in teaching and learning that hosted 135 in-person and 329 virtual attendees from 43 institutions.

Team leads have had many opportunities to lead GenAI efforts at their institutions, leveraging their learning and experience as collaborators on the MegaSoTL-AI project. Across the board, they have found themselves taking on more active (leadership) roles in AI conversations and are increasingly seen as a resource to their colleagues. Participation in the collaboration catalyzed a shift in how several team leads understood their professional roles, moving from contributors within a research project to recognized leaders in AI-related teaching and learning on their home campuses. Five collaborators are community resources or the "point-person" for GenAI-related questions. As one team lead explained:

> …now I'm definitely the sort of lead in our team in terms of AI-related programming… doing content development, literature review, everything is very beneficial for me [for the project], but also at the same time, very important to the work that I' m currently doing [in my professional role]. So, I wouldn't see this as something separate from what I do. This is actually well integrated into my current job.

This integration of project work into participants' everyday professional roles enabled leadership around GenAI to diffuse outward from the collaboration into departments, programs, and institutional initiatives.

As a result of this role shift, several team leads were subsequently invited to contribute to institutional policy development, lead workshops, and serve as point people for AI-related questions. Three project leads have been invited speakers on topics related to their research projects, three have contributed to development of institutional policy and guidelines in an official capacity (e.g., as a member of the AI Composition Guidelines for Composition Program; an ad hoc committee in School of Communication Studies that is developing an AI policy statement; as a board member for the Harrisonburg School AI initiative), and six have offered workshops or facilitated programs beyond the activities supported by the MegaSoTL project. These outreach efforts show clear growth in the perception of team members as knowledgeable experts and initiatives for ethical and scalable AI integration. Importantly, it is not only the cross-institutional nature of this work that matters, but also its inclusivity across roles. Too often, participation in large-scale, grant-funded projects is limited to a narrow band of participants, often privileging full-time faculty and limiting opportunities for staff and graduate students to contribute as co-investigators or leaders. In contrast, our model deliberately involved faculty, staff, educational developers, postdoctoral research associates, and graduate students, creating teams that could address the complexity of GenAI from multiple vantage points. This diversity, a unique characteristic of this project, fostered a grassroots movement, where conversations about AI policy, pedagogy, and practice were shaped simultaneously from the classroom level upward and from institutional policy downward. As one collaborator reflected:

> I like the openness of this, that everybody is welcomed [including] staff and graduate students, rather than often when it comes to a grant project, they will say, oh, only faculty members can do it. Often staff even don't have opportunities to collaborate with them, or being the PI, for example. So, I really appreciate this opportunity and the openness of this program.

This openness translated into a stronger sense of ownership over both the research process and the resulting resources, particularly among collaborators whose roles are often peripheral in institutional initiatives. Involving instructors in the design of collaborative research and resource development ensured that the resulting projects and tools were not abstract recommendations imposed from outside, but context-sensitive solutions. At the same time, the distributed model enabled staff and graduate students—groups often excluded from this work—to contribute as co-creators and experts. By weaving together perspectives from multiple roles and institutions, the project moved beyond a patchwork of siloed efforts toward a more coherent and scalable model.

Establishing Clear Expectations, Roles, and Responsibilities

Another important consideration when launching a project of this scope is to ensure enough time is dedicated to establishing the structure and relationships within the collaboration. Given the diverse roles and institutional contexts of the collaborators, we as PIs had to develop a structure within which the collaboration could exist. This approach included identifying a common tool for communication and file sharing among and between research teams, initiating regular communication with team members, identifying tools and developing processes for project management including planning and tracking of tasks as well as developing clear guidelines for roles and responsibilities. The leaders of this collaboration, the PIs, met weekly to discuss progress, each of us taking the lead in various aspects of the project to ensure tasks were completed and appropriate team members were connected. Several project tracking documents were used to track the progress of the research teams and grant activities. Despite these initial project management pieces, we overestimated the previous experiences of the collaborators in working on cross-disciplinary and cross-institutional teams, believing that past skills and experience in conducting disciplinary research would translate easily into this project. We found, however, that for most team members and team leads, the scale of this project and the challenges of truly working cross-institutionally were new. As one collaborator explained:

> Sometimes we want to jump right into the project and get started, but I think for this, because it involves so many collaborators and people with various interests, I think it would be helpful to devote more time for project planning to really understand the scope and then figure out more efficient ways of working on things.

In response to this feedback, we developed a clear roles and responsibilities document to use when new collaborators and projects are added. This document now serves as a standard onboarding tool for new collaborators, and includes our responsibilities as PIs, the expectations of team leads and members, and policies related to ownership and dissemination of the materials developed through the collaboration. As we initiate future phases where new collaborators join the project, we plan to provide some training on the basics of project management to all team members and to build in time for connection and relationship development among collaborators.

Recognition of How our Model May Look Different in Different Contexts

While our statewide collaboration demonstrates the promise of cross-institutional networks, we recognize that the model will look different in other contexts. Institutional cultures, governance structures, and available resources shape the feasibility and form of collaboration. For example, state systems with centralized oversight may be able to streamline IRB processes or resource allocation more easily than consortia of independent institutions. In contrast, private institutions or community colleges may need to adapt the model by scaling down the number of partners or focusing on discipline-specific collaborations. Equally important, the model requires flexibility. One collaborator noted the importance of “being flexible and receptive to [the fact] that this is a ‘learning as we go’ process,” and our experience as PIs certainly affirms this assertion.

Replicable Change Model

A key insight from this initiative is the catalytic role of educational development in responding to pedagogical disruptions that demand rapid yet thoughtful institutional responses. While our model was built in response to GenAI, its structure is not technology-specific. Rather, the model demonstrates how CTLs and educational developers can mobilize existing networks, facilitate inclusive inquiry, and translate findings into resources that address urgent challenges at scale.

In this sense, GenAI served as a testing ground for a broader collaborative model. The same infrastructure of cross-institutional partnerships, cross-role teams, and inquiry-to-resource pipelines could just as effectively be mobilized to respond to other disruptions, such as the rapid pivot to online teaching during COVID, future technological shifts, or other pedagogical reforms related to assessment or student success. By convening stakeholders across institutional roles and contexts, CTLs provide the connective tissue necessary to move from reactive, isolated decision-making toward proactive, research-informed responses. This adaptability is crucial because higher education will continue to encounter disruptions that are unpredictable in timing and scope. By investing in educational development as a site of collaboration, institutions position themselves not only to address the immediate challenge of GenAI, but to strengthen long-term capacity for innovation, resilience, and ethical decision-making.

Dedicated Resources

To be successful, these collaborations need time, money, and resources. Access to reassigned time for full-time staff and faculty members and direct funding for part-time faculty, staff, and graduate students help ensure that all interested participants can be part of the work. Less tangible but equally valuable are expressions of support from institutions. One way that administrators can support these collaborations is by ensuring that other university offices (e.g., research ethics offices, research funding offices) are familiar with and prepared to support this type of work effectively. Additionally, highlighting the important work of the project throughout the institution and within the administrators' spheres of influence (e.g., professional networks) outside the institution can help support the work of the collaboration through increased visibility, finding partners, and positioning the individuals involved with the collaboration as potential leaders.

Conclusions

This statewide initiative demonstrates that a coordinated, ethical, and scalable response to generative AI in higher education is not only possible, but is strengthened when leadership is distributed, inquiry-driven, and rooted in existing networks. By positioning Centers for Teaching and Learning as strategic hubs, the project created space for faculty, staff, students, and administrators to move beyond reactive policymaking and ad hoc integration toward proactive, research-informed practice. Instructor-led investigations generated resources that were adaptable across diverse institutional contexts and grounded in the lived realities of teaching and learning. Investing in this type of networked collaboration yields benefits that extend far beyond the immediate scope of AI integration. Participants developed expertise, assumed leadership roles on their campuses, and built professional relationships that will support future innovations. CTLs proved uniquely positioned to convene cross-role teams, translate research into actionable tools, and sustain momentum through shared ownership of outcomes. As institutions continue to grapple with the rapid evolution of AI, this collaborative model offers a replicable roadmap: start with faculty-led inquiry, leverage cross-institutional partnerships, embed ethical considerations at every stage, and use CTLs as the connective tissue between research and practice. For state systems, regional consortia, and multi-campus universities, this model illustrates how moving from silos to synergy can build the internal capacity, agility, and ethical grounding necessary to navigate technological change with nuance and foresight.

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