



Leading with Purpose: Artificial Intelligence and the Future of Higher Education

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LEADING WITH PURPOSE: ARTIFICIAL INTELLIGENCE AND THE FUTURE OF HIGHER EDUCATION

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EXECUTIVE SUMMARY

Generative artificial intelligence (AI) is becoming an increasingly visible part of higher education. According to the [ACE 2025 Fall Term Pulse Point Survey](#), 25 percent of responding institutions reported that they had already adopted generative AI for student learning, and an additional 65 percent expected to adopt it within the next two years. This rapid uptake does not necessarily mean institutions are ready to use AI effectively. Many colleges and universities are still building the governance structures, data practices, faculty and staff capacity, and evaluation processes needed to use AI responsibly.

For institutional leaders, AI is not only a technology issue; its use now influences teaching and learning, advising and student support, assessment, data governance, procurement, accessibility, equity, and public confidence in higher education. The challenge is less about deciding whether to use AI than about deciding where it genuinely improves learning—and where human judgment should remain central. Leaders must continually balance competing priorities: expanding support without weakening meaningful human connection, improving efficiency without sacrificing equity, respecting faculty discretion while maintaining institutional coherence, and acting quickly without abandoning thoughtful governance. Those are leadership decisions—not technology decisions.

This paper provides a framework for leaders to guide their institutions forward as technology continues to evolve and examines AI's implications in three use cases where its effects on the student experience are especially immediate:

- **Personalized learning.** AI may support more timely feedback, practice, and individualized learning assistance. Its value will depend on whether institutions use it to strengthen active learning, faculty expertise, student agency, and opportunities for meaningful interaction.
- **Advising and student success.** AI may help institutions expand access to routine information, support outreach, and assist advisors and other staff in responding to student needs. These uses require attention to data quality, privacy, accuracy, accountability, and clear pathways to human support.
- **Assessment.** Generative AI is prompting institutions to reconsider how they assess learning and communicate expectations for AI use. Detection tools have limitations and should not be the sole institutional response to academic integrity concerns. Institutions may need to support faculty in developing assessment approaches that provide meaningful evidence of learning and help students use AI critically and responsibly.

The paper draws on two sources of evidence: 10 semi-structured interviews with higher education leaders and a review of academic and practitioner literature related to AI, learning, student success, assessment, and institutional strategy. Interviewees represented a range of roles and institutional contexts. Interviews were conducted on an anonymous basis to encourage participants to speak candidly about their experiences, perspectives, and institutional practices, particularly given the rapidly evolving and sometimes sensitive nature of decisions surrounding AI in higher education. Their observations should not be seen as representative of the entire sector but are presented as informed perspectives and examples of emerging practice.

Across the three use cases, several common themes emerge:

- **Building institutional foundations.** Responsible AI use depends on accurate data, secure systems, clear policies, accessibility, privacy protections, and clear accountability. Institutions should distinguish between lower-risk experimentation and the use of applications that involve sensitive student data, consequential decisions, or broad deployment.
- **Supporting faculty and staff in AI implementation.** Faculty, advisors, instructional designers, technology leaders, and student-support professionals play central roles in determining whether AI supports institutional goals. Sustained professional learning, time for course and assessment redesign, and opportunities to share practice are important conditions for responsible use.
- **Keeping equity at the center.** AI may expand users' access to feedback, information, and support, but its benefits will not be distributed automatically. Institutions should consider who is likely to benefit, who may

encounter barriers or new risks, and what additional support is needed to ensure that AI-enabled practices advance equitable outcomes.

- **Evaluating AI through the institution's mission.** Financial considerations matter, but institutions should evaluate AI initiatives in relation to the outcomes they seek to advance—student learning, student success, access, faculty and staff support, privacy, accessibility, equity, and institutional autonomy. Clear measures of success should be established before pilots begin, and institutions should proceed with a willingness to refine, scale, or discontinue initiatives based on evidence.

There is no single model for responsible AI adoption. Institutions differ in mission, resources, governance, student populations, technology infrastructure, and community relationships. A community college, tribal college, regional public university, and large research university will face similar questions but will make different, context-specific choices in response.

The paper's findings identify several priorities for institutional leaders seeking to move from isolated experimentation toward coordinated, mission-aligned action.

1. Define the student and institutional outcomes that AI initiatives are intended to advance.
2. Establish cross-functional governance and clear accountability for AI-related decisions.
3. Set transparent expectations for AI use in teaching, learning, advising, and assessment.
4. Invest in sustained faculty and staff development connected to disciplinary and institutional needs.
5. Strengthen data governance, privacy, cybersecurity, accessibility, and vendor-review practices.
6. Design and evaluate AI-enabled services with equity, belonging, and human connection in mind.
7. Pilot thoughtfully, measure outcomes, and share lessons across the sector.

Finally, it is worth noting that this paper reflects the context and data that was available in 2026. AI will continue to evolve, and institutions will need to adapt as evidence, technology, and students' needs change. There may also be questions or considerations that could not be anticipated in this document, particularly given how quickly the technology is advancing. Institutions facing this moment do not need to pursue AI use for its own sake. The opportunity lies in building institutional capacity—the ability to make timely, accountable decisions that use AI in service of learning, student success, and the public purpose of higher education, even as the technology continues to evolve. The work of building capacity for effective AI use requires shared governance and broad expertise, but it also requires sustained senior leadership. Above all, it requires institutions to keep AI decisions grounded in mission, educational purpose, and the needs of the students and communities they serve.



INTRODUCTION—THE MOMENT, THE EVIDENCE, AND THE QUESTIONS AHEAD

Generative AI is becoming an increasingly visible part of higher education. It is affecting how students approach academic work, how faculty consider teaching and assessment, how institutions provide information and support to their stakeholders, and how leaders address data, technology, and governance.

The ACE [2025 Fall Term Pulse Point Survey](#) indicates that many institutions are already using or planning to use generative AI for student learning. Twenty-five percent of responding institutions reported that they had already adopted generative AI for this purpose, and an additional 65 percent expected to adopt it within the next two years. And in the past year, even more institutions have likely shifted into AI planning and use. These findings indicate substantial institutional interest and activity. They do not—by themselves—establish that institutions have the policies, infrastructure, faculty and staff capacity, or evaluation practices needed for responsible implementation.

Institutional leaders must determine where—and under what conditions—AI can advance institutional missions. This requires attention to student learning and success, faculty and staff roles, data privacy and security, accessibility, equity, institutional autonomy, and public trust. The appropriate approach will vary by institution, since colleges and universities differ in mission, resources, governance structures, student populations, technology infrastructure, and community relationships.

Preparing higher education for AI requires institutions to address a set of interconnected questions, beginning with purpose: what are we trying to accomplish with AI and learner data and for whom? The next questions to address are about what data are needed, how those data should work across institutional systems, what governance and ethical principles should guide their use, what institutional capacity is needed to manage them responsibly, and what infrastructure can support those goals. Building shared data infrastructure is much like building a system of highways. Highways are important, but they are built only after there is a clear understanding of where people need to go and what communities they are intended to connect. In much the same way, higher education cannot begin with large-scale data sharing before there is agreement about what learner data are needed, how those data should work across institutional systems, what governance and ethical principles should guide their use, and what institutional capacity is needed to manage them responsibly.

Efforts such as the [1EdTech interoperability standards](#) are an important step toward technical interoperability, but those efforts alone do not answer the larger questions of governance, educational purpose, or learner-centered data stewardship. These considerations suggest that the conversation about AI should begin not with infrastructure but with institutional purpose. Throughout this paper, the emphasis is therefore on the leadership questions institutions must address, including mission, governance, learner outcomes, institutional capacity, and trust, because those decisions will ultimately shape what kinds of infrastructure are needed and how they should be developed to serve higher education.



SECTION 2: THE LANDSCAPE

AI-related decisions are being considered alongside other institutional priorities. In the [ACE 2025 Fall Term Pulse Point Survey](#), senior leaders reported concern about public perceptions of the value of college, student mental health, academic freedom and institutional autonomy, long-term financial viability, and enrollment. AI does not replace these priorities, but it may intersect with them in different ways depending on how institutions use it.

For example, decisions about AI in teaching and assessment may raise questions about faculty authority, academic integrity, and the evidence institutions use to evaluate student learning. Decisions about AI-enabled student support may raise questions about access, accuracy, privacy, and the role of human relationships in advising. Decisions about enterprise systems or vendor tools may require attention to data governance, cybersecurity, procurement, and financial stewardship.

The pace of technological change creates a practical challenge. Institutions may need to make decisions while the capabilities, limitations, and institutional uses of AI continue to evolve. At the same time, students, faculty, and staff are already encountering AI tools in academic and professional contexts. A mission-aligned response requires neither uncritical adoption nor blanket restriction. It requires clear goals, appropriate safeguards, informed experimentation, and ongoing evaluation. Institutions do not need to move quickly on every tool or use case, but they do need the capacity to make timely decisions as students, faculty, staff, and vendors continue to introduce AI into academic and institutional life. Deferring all decisions until the technology stabilizes is not a neutral choice; it can allow consequential AI use practices to develop without establishing shared expectations, adequate safeguards, or accountability.

2.1 PURPOSE AND SCOPE

This paper examines AI's implications for three areas in which its effects on the student experience and academic missions are especially immediate:

1. **Personalized learning.** AI may support feedback, practice, and other forms of individualized learning assistance. Its use also raises questions about active learning, student agency, faculty expertise, accessibility, and the social dimensions of education.
2. **Advising and student success.** AI may help institutions provide routine information, support outreach, and assist staff in responding to student needs. These uses require attention to data quality, privacy, accuracy, accountability, equitable access, and pathways to human support.
3. **Assessment.** Generative AI is prompting institutions to reconsider how they evaluate student learning and communicate expectations for AI use. This includes questions about academic integrity, assessment design, faculty development, and the knowledge and judgment students need in an AI-enabled environment.

These areas do not encompass every way that AI may affect higher education. AI also has implications for institutional operations, research, workforce development, and other functions. The paper focuses on personalized learning, advising and student success, and assessment because each is closely connected to the academic mission and to students' experiences of higher education.

This paper does not offer a single model for adoption. Instead, it identifies questions, emerging practices, and institutional considerations that may help leaders develop approaches suited to their own contexts.

2.2 EVIDENCE AND METHODOLOGY

This paper draws on two complementary sources of evidence:

1. **Interviews with higher education leaders.** ACE conducted 10 semi-structured interviews in early 2026 with leaders whose experience spans campus-level AI implementation; institutional leadership; system-level strategy; teaching and learning; assessment; research; philanthropy; and educational technology. Participants represented a range of institutional types and perspectives, including large public research universities; regional public institutions; community colleges and college systems; a tribal college; and a private medical university.

Interview Participants

This paper draws on interviews with leaders from across higher education and philanthropy, including:

- **University Chief Information Officers (CIOs) and Chief Technology Officers (CTOs)** – Leading enterprise AI infrastructure, data governance, and institution-wide technology strategy
- **College and University Presidents** – Aligning AI adoption with institutional mission, resources, governance, and community priorities
- **System-Level Higher Education Leaders** – Coordinating AI strategy, policy, and implementation across multi-campus systems
- **Directors of Teaching and Learning (Centers for Teaching and Learning)** – Supporting faculty, instructional innovation, and AI integration in teaching and learning
- **Assessment and Institutional Improvement Leaders** – Exploring AI-enabled approaches to assessment, feedback, and institutional effectiveness
- **Higher Education Scholars and Philanthropic Leaders** – Studying sector-wide trends, funding innovation, and identifying emerging opportunities and risks

This range of perspectives is important because AI-related decisions are experienced differently across institutional contexts. The opportunities, risks, and implementation challenges described in this paper may look different at a large research university, a community college, a tribal college, or a regional public institution. Interviewees' observations are presented as informed perspectives and examples of emerging practice—not as representative of the entire sector or as evidence of a sector-wide consensus.

Academic and practitioner literature. This paper also draws on the sources listed in the references section, including institutional surveys and literature on AI and computer-assisted instruction, personalized learning, learning analytics, advising and student success, assessment, information literacy, and institutional strategy. The purpose of this literature review is to provide context for emerging institutional questions; it does not treat early examples of AI use as conclusive evidence of effectiveness.

Because generative AI is evolving rapidly, some practices described in this paper remain in an early stage of use. Institutions should evaluate AI practices and applications carefully in their own settings as additional evidence becomes available.

2.3 HOW TO READ THIS PAPER

The following sections of this paper examine personalized learning, advising and student success, and assessment. Each section describes relevant evidence and interview perspectives, identifies institutional considerations, and outlines questions leaders may use to guide decision-making.

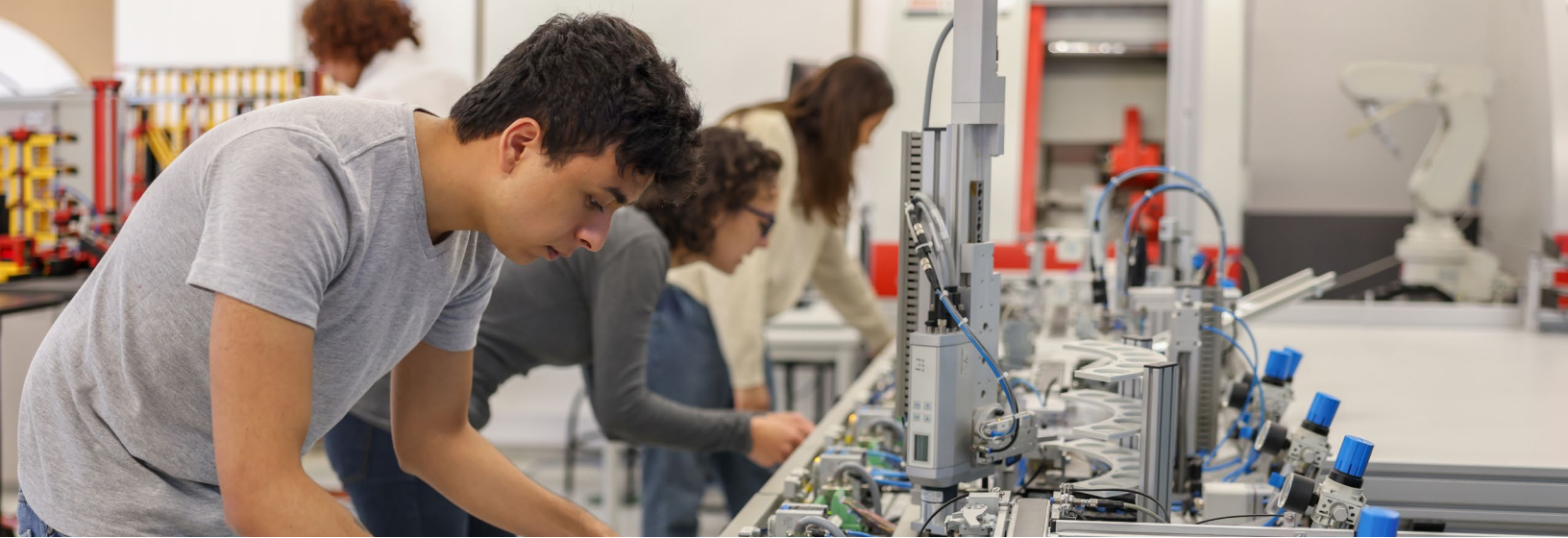
Across all three areas, several questions recur:

- What student or institutional outcome is the AI-enabled practice intended to improve?
- What human judgment, expertise, or relationship must remain central?
- What data, privacy, accessibility, security, and governance safeguards are required?
- Who is likely to benefit, and who may face new barriers or risks?
- What evidence will help the institution decide whether to refine, scale, or discontinue an initiative?

The questions in this paper are difficult to answer because they involve trade-offs rather than technical fixes. An AI-enabled practice may:

- Expand students' access to support while reducing opportunities for meaningful interaction with faculty or staff
- Reduce routine administrative work while creating risks for privacy or accuracy
- Increase consistency across services while narrowing professional discretion

Institutional leaders cannot eliminate these tensions. Their task is to make them visible, weigh them against institutional missions, and revisit decisions as evidence develops.



SECTION 3: HISTORICAL PARALLELS—LESSONS FROM THE CURRENT MOMENT

Generative AI differs from earlier educational technologies in important ways: it is broadly accessible, rapidly evolving, and capable of producing text, images, code, and other forms of content that have traditionally been treated as evidence of student work and learning. Still, the questions it raises in higher education are not entirely new. Across prior technology transitions, institutions have had to determine how new tools should support learning, how faculty roles should evolve, how students should demonstrate knowledge, and how institutional policies and practices should respond.

Several interviewees drew these connections directly. One scholar of educational technology characterized generative AI as a consequential development on the scale of the internet or smartphones, while emphasizing that higher education has experience adapting to significant technological change. A system-level leader described current debates over AI professional development as echoing earlier debates about online instruction, particularly the principle that technology should serve pedagogy rather than determine it.

These parallels do not provide a blueprint for AI adoption; they do identify recurring institutional questions:

- How should technology support learning?
- What capabilities do faculty, staff, and students need?
- How can institutions expand access without weakening meaningful human support?
- How should assessment evolve when technology changes the conditions under which students produce academic work?

3.1 FROM INFORMATION ACCESS TO CRITICAL USE

As internet access and digital information resources expanded during the 1990s and early 2000s, colleges and universities increasingly recognized that students needed more than the ability to locate information—they also needed to evaluate its quality and use it responsibly. The Association of College and Research Libraries' *Information Literacy Competency Standards for Higher Education* identified the ability to determine needed information, access it effectively, evaluate sources and information critically, and use information responsibly as core competencies (ACRL 2000). Building on this perspective, Bruce (2004) argued that information literacy should be understood not simply as a set of technical skills but as a catalyst for broader educational change.

Generative AI extends this challenge. Students may now use tools that can produce credible-sounding responses, summaries, images, and analyses in seconds. Access alone does not ensure that students can assess the quality, accuracy, or appropriateness of those outputs. The relevant educational task is to help students develop the judgment to evaluate AI-generated material, recognize its limitations, and use it responsibly in support of learning.

This work builds on longstanding institutional efforts to help students locate, assess, and use information. The new challenge is the degree to which AI can participate in the production of academic work and the speed with which students can rely on it.

3.2 PERSONALIZATION: THE PROMISE OF SUPPORT AT SCALE

Educators' aspiration to provide more individualized learning support to students predates generative AI. Carbonell (1970) proposed an artificial intelligence approach to computer-assisted instruction, and Bloom (1984) identified one-to-one tutoring as a powerful benchmark for improving learning outcomes. Subsequent research has examined both intelligent tutoring systems and other forms of technology-supported tutoring. Koedinger and Aleven (2007) described the "assistance dilemma" in cognitive tutoring: providing assistance can help learners complete tasks, but it can also reduce opportunities for productive problem solving. VanLehn (2011) compared the effectiveness of human tutoring, intelligent tutoring systems, and other tutoring approaches.

More recent research on personalized learning offers promising—and qualified—evidence. Pane et al. (2015) reported positive evidence associated with personalized-learning approaches, while Márquez et al. (2024) identified both the growing adoption of learning analytics in higher education and the institutional challenges involved in implementing it. Together, these sources suggest that personalization will not be achieved with a single intervention or technology. Its effectiveness depends on instructional design, the quality and use of data, and the ways in which educators integrate technology into teaching and learning.

The experience of massive open online courses (MOOCs) offers related caution. Khalil and Ebner (2014) documented low completion rates in MOOCs and considered approaches to improving retention. MOOCs are not equivalent to AI-enabled learning, and their completion rates should not be used to predict AI outcomes. The challenges in making MOOCs successful do, however, underscore that broad access to digital content does not by itself ensure persistence or learning.

The value of AI-enabled personalization depends on whether it strengthens students' active engagement with learning while complementing—not displacing—faculty expertise, instructional design, and meaningful interaction.

3.3 ADVISING: EFFICIENCY, COORDINATION, AND HUMAN CONNECTION

The evolution of student-service delivery also offers useful context for considering AI for advising purposes. Bailey et al. (2015) documented the challenges students face when navigating complex college pathways without coordinated institutional guidance. Their work helped inform the Guided Pathways movement, which emphasizes clearer program structures and more proactive support.

AI may enable institutions to answer routine questions, identify patterns that warrant outreach, and extend access to information outside traditional office hours. These applications may be especially relevant where advising capacity is limited. Research on advising also suggests that effective student support depends on more than timely access to information. Students benefit from coordinated services, meaningful connections with advisors, and clear pathways to support. Bharadwaj et al. (2023) documented challenges related to advising caseloads, coordination among student-support services, advisor turnover, and students' sense of connection to their institutions. Flaherty (2023) similarly reported that many students experience gaps in access to academic advising and guidance.

The lesson is not that institutions should reject self-service or automated support. Rather, they should consider how technology changes the points at which students encounter help. AI-enabled advising may increase access to transactional information, but institutions will still need to ensure that students can reach advisors and other staff when they need judgment, advocacy, problem solving, or relationship-centered support.

This consideration has implications for equity. The students who are least familiar with institutional processes may be least well served by systems that assume they can identify problems and seek help independently. Institutions should therefore assess whether AI-enabled advising expands meaningful support for students or merely shifts responsibility for navigating complex systems onto them.

3.4 ASSESSMENT: FROM DETECTION TO DEMONSTRATION OF LEARNING

Concerns about technology and academic integrity also have a long history. Noble (1998) criticized the commercialization and automation of higher education associated with early online learning. Simmons (1999) examined competing ideas about authorship, plagiarism, and cheating, showing that these concerns predate the internet, even as digital technologies changed their form.

Generative AI intensifies current assessment questions because it can produce work that may resemble conventional student outputs. In interviews for this paper, several leaders expressed concern about relying on AI-detection tools as the primary institutional response.

One interviewee submitted writing he had produced himself to an AI-detection tool and received a result indicating, with 98 percent confidence, that the writing was AI-generated. This single experience does not establish the accuracy of detection tools generally. It illustrates why institutions should be cautious about relying on any one tool as conclusive evidence of authorship. Another interviewee argued that institutions should focus on assessment design and student learning rather than treating detection as a complete solution. These observations do not mean that all detection tools are ineffective in every setting. They do point to the limits of a detection-only approach.

Institutions may need to clarify expectations for AI use and support assessment practices that enable students to demonstrate understanding, apply knowledge, explain their reasoning, and reflect on their work.

This shift also places new demands on faculty. It requires time, professional development, and support for course and assessment redesign. It may also require institutions to identify which foundational skills students should demonstrate independently and where AI-supported work can be incorporated transparently and appropriately.

3.5 THE INSTITUTIONAL LESSON

Earlier technology transitions do not resolve the questions posed by generative AI. They do suggest that sustainable adoption depends on more than the capabilities of a tool. Institutions need to connect technology decisions to educational purpose; support faculty and staff; establish clear expectations for students; attend to access, equity, and student experience; and evaluate whether new practices advance intended outcomes.

These lessons inform the three sections that follow. In personalized learning, advising and student success, and assessment, the core leadership task is to determine how AI can support institutional missions while preserving the human judgment, relationships, and learning processes that remain central to higher education.



SECTION 4: PERSONALIZED LEARNING—PROMISE, CONDITIONS, AND INSTITUTIONAL CHOICES

“What I worry about with personalized learning is it sounds isolating....I worry that we’re setting up a situation where all the responsibility and burden is put on students, and they’re isolated from other students, and therefore they’re not going to be given the transformative educational experience that we want them to have.”

— Interview participant

The aspiration to provide more individualized learning support has long been part of educational technology. Early work on AI and computer-assisted instruction anticipated the possibility of systems that could respond to individual learners (Carbonell 1970). Bloom’s (1984) “2 Sigma Problem” later established one-to-one tutoring as a powerful benchmark for improving learning outcomes, while also underscoring the difficulty of providing that level of support at scale. Research on cognitive tutors and intelligent tutoring systems has continued to examine how technology can support learning, including the question of when assistance helps students and when it may reduce opportunities for productive problem solving (Koedinger and Aleven 2007; VanLehn 2011).

Generative AI has renewed institutional interest in personalized learning because it may make certain forms of individualized feedback, practice, and support more widely available. Yet personalization is not a single tool or intervention. Its value depends on how institutions define learning goals, design the instructional experience, protect student data, support faculty and staff, and evaluate whether the approach improves outcomes for students.

4.1 EMERGING USES AND INSTITUTIONAL EXAMPLES

Interviewees described several ways institutions are beginning to explore AI-enabled personalized learning. These examples should be understood as emerging practices—not as generalizable evidence of effectiveness.

At one large public institution, a technology leader described significant investment in AI infrastructure, including work to connect course content and student information systems. He emphasized that the technical capacity exists in some areas but that production use depends on governance, interoperability, data-sharing standards, and Family Educational Rights and Privacy Act (FERPA)-related safeguards. More broadly, this example highlights an important institutional reality: for personalized learning to operate responsibly at scale, institutions need more than AI tools. They need clear data-governance practices, secure infrastructure, and shared expectations about how student information may be used.

A community college president described efforts to embed AI tutors and teaching assistants into course shells as part of a broader learning management and digital workflow strategy. The goal was not simply to introduce AI tools but to provide faculty—particularly new or adjunct instructors—with structured course supports that could promote greater consistency in the student learning experience.

A system-level leader described culturally contextualized AI applications, including assignments and tools designed to reflect the communities and institutional contexts in which students learn. This example points to an important design consideration: personalization should not be limited to pace or content sequencing. It may also involve relevance, context, and the ways students see their identities, communities, and goals reflected in learning.

An assessment leader described using a custom Generative Pre-Trained Transformer (GPT) to provide richer and more timely qualitative feedback on student work, while retaining human review and judgment in the assessment process. This example suggests one potentially high-value use of AI: supporting formative feedback in ways that help students revise, reflect, and improve.

These examples show that AI-enabled personalization is already being explored across different institutional settings. They also show that the most consequential questions are institutional and pedagogical, not merely technical.

4.2 INFRASTRUCTURE AND GOVERNANCE CONDITIONS

Personalized learning depends on data. To tailor feedback, identify gaps, or recommend learning supports, institutions need access to accurate, well-governed information about courses, learning activities, student progress, and student support systems. Many institutions do not yet have the integrated infrastructure required to do this work responsibly or at scale.

Interviewees repeatedly described infrastructure and governance as central constraints. One technology leader described AI systems that were technically possible but not yet ready for full deployment because the institution still needed appropriate governance frameworks, interoperability standards, and data-protection practices. Another described challenges associated with fragmented institutional systems and the absence of a mature data warehouse. A tribal college president described a different institutional context, where the transition from paper-based to digital systems and concerns about data ownership and sovereignty shaped the pace and terms of AI adoption.

These examples underscore that institutional readiness varies significantly. Well-resourced institutions may be better positioned to build integrated AI systems, while institutions serving many students from underserved backgrounds may face greater capacity constraints. Without deliberate attention, AI-enabled personalization could widen gaps between institutions that have the resources to build governed data ecosystems and those that do not.

For leaders, the infrastructure question is therefore also an equity question. Institutions should assess whether they have the data quality, privacy protections, accessibility practices, cybersecurity safeguards, and faculty support needed before scaling personalized-learning tools.

4.3 PRESERVING ACTIVE AND SOCIAL LEARNING

Interview Perspective: Personalization Without Isolation

A higher education research leader cautioned that some approaches to personalized learning can place too much responsibility on individual students. In this view, a model centered on students moving independently through individualized pathways may reduce opportunities for peer learning, faculty interaction, and participation in a shared educational community. The concern is not that personalized support is inherently harmful; it is that institutions should consider whether AI-enabled learning tools strengthen or weaken the relationships and learning environments that contribute to student engagement and success.

Personalized learning can be appealing because it suggests that each student might receive support matched to their needs. But several interviewees raised a concern that personalization—if poorly designed—can isolate students or shift too much responsibility onto individual learners. Personalized learning should not be evaluated only by whether students receive more individualized content or faster feedback. Institutions should also consider whether AI-enabled approaches strengthen or weaken students' connection to faculty, peers, and meaningful learning communities.

Learning science supports the importance of social context. Moss (2003), drawing on sociocultural views of learning, emphasizes that learning involves not only acquiring knowledge and skill but also participating in communities of practice and developing identity within those communities. The key question is not whether institutions should personalize learning; instead, we should ask what kind of personalization advances the institution's educational mission. AI-supported learning should strengthen—not replace—the active, relational, and social dimensions of education.

4.4 SUPPORTING LEARNING WITHOUT REPLACING THE LEARNER'S WORK

A second concern is that AI may make it easier for students to produce polished work without developing underlying understanding. Interviewees described this risk in different ways. One community college president noted that students who are not taught how to use AI may use it to complete work rather than support their learning. Another leader compared overreliance on AI to sending “the robot to the gym” on one's behalf—the work may be completed, but the learner does not develop the capacity the work was designed to build. The relevant distinction is not necessarily between AI use and no AI use but between assistance that helps students practice, receive feedback, and exercise judgment and assistance that performs the cognitive work the learning activity is intended to develop.

This concern aligns with research and emerging frameworks that distinguish between support for cognition and replacement of cognition. Ayodele et al. (2026) propose an Augmented Cognition Framework that distinguishes between individual cognitive work and distributed work across a human-AI system. Their framework emphasizes that effective AI use depends on the learner's ability to direct, evaluate, and integrate AI outputs. Without underlying competence, students may produce fluent work without durable understanding.

For personalized learning, this suggests that AI may be most valuable when it supports productive struggle rather than eliminating it. Examples include formative feedback, targeted practice, adaptive remediation, and prompts that help students identify gaps in their understanding. Uses that generate complete answers or substitute for the student's intellectual work should be approached more cautiously, especially when the purpose of the assignment is to build foundational knowledge or skill.

Faculty support is essential here. Institutions should help instructors distinguish between AI uses that deepen learning and those that may undermine it. That support should begin with learning goals—not tools. As one teaching and learning leader emphasized, institutions already have research-grounded approaches to effective instruction; AI should be integrated into those approaches rather than treated as a replacement for them.

4.5 WHAT THIS MEANS FOR LEADERS

Personalized learning is not primarily a technology decision. It is a teaching, learning, infrastructure, and governance decision with technology implications. Institutions considering AI-enabled personalization should begin with the educational outcomes they are trying to improve and the student populations they aim to serve.

Leaders should consider the following questions:

- What learning problem is the AI-enabled approach intended to address?
- How will the tool support active learning, feedback, practice, and student agency?
- What human relationships—faculty, peer, advising, or mentoring—must remain central?
- What student data are required, and how will privacy, security, accessibility, and data quality be protected?
- Who is likely to benefit, and who may be disadvantaged if the tool is scaled?
- What evidence will determine whether the approach should be revised, expanded, or discontinued?

The promise of AI-enabled personalized learning is real, but it is conditional. It depends on whether institutions use AI to advance learning, strengthen support, and expand opportunity while preserving the human judgment and relationships that remain central to higher education.



SECTION 5: ADVISING AND STUDENT SUCCESS— EXPANDING SUPPORT WHILE PRESERVING CONNECTION

Advising is a central part of how institutions help students navigate academic requirements, make informed choices, connect with resources, and persist toward completion. Yet many students do not receive the guidance they need. Flaherty (2023) reported that nearly half of students surveyed lacked key academic guidance or avoided advising. Research on community college reform has also documented the challenges students face when they must navigate complex institutional pathways without clear, coordinated support (Bailey et al. 2015).

AI may offer institutions new ways to extend student support. AI-enabled tools can respond to routine questions, help students locate information, support outreach, and assist staff in identifying patterns that may warrant attention. These uses may be especially relevant for institutions with high advising caseloads or for students whose work, family, or transportation responsibilities make it difficult to access support during standard office hours.

At the same time, advising is not only an information delivery function. It can be a relationship through which students receive encouragement, make sense of institutional expectations, and connect to academic, financial, and personal support. The leadership challenge is to determine where AI can expand access and reduce administrative burden while ensuring that students retain meaningful pathways to human guidance.

5.1 EMERGING USES OF AI IN ADVISING AND STUDENT SUPPORT

Interviewees described a range of possible and emerging applications. These examples are not evidence of effectiveness across all settings; they illustrate the types of questions institutions are beginning to address.

A community college president described AI as a potential source of around-the-clock support for students managing work, family, and financial responsibilities. In this view, AI may help students obtain routine information at times when an advisor or office is unavailable.

A system-level leader described continued experimentation with AI tools that could support student services while emphasizing the need to test new capabilities in controlled environments before connecting them to live student data. This approach reflects the potential value of experimentation alongside the need for clear boundaries around implementation.

An assessment leader emphasized that AI-generated advice can create risks when information is inaccurate, incomplete, or applied without sufficient context. This concern is especially important in advising, where errors can affect course selection, financial decisions, academic standing, or access to services.

These perspectives suggest that the most immediate uses of AI may be in supporting routine information and administrative workflows. Whether institutions use AI more broadly in advising should depend on the quality of the information available, the safeguards in place, and the extent to which staff can review and act on the insights a system produces.

5.2 ADVISING AS BOTH SERVICE AND RELATIONSHIP

Interview Perspective: When a Routine Question Is Not Routine

AI-enabled advising may help students obtain routine information outside standard office hours, which can be especially valuable for students balancing work, family, and other responsibilities. At the same time, an interviewee emphasized that a question about registration, financial aid, or degree requirements can sometimes be an opening into a broader conversation about a student's circumstances, confidence, or sense of belonging.

For institutions, the implication is not that the process of responding to routine questions should remain entirely face-to-face. It is that automated support should include clear pathways to advisors and other professionals when students need judgment, advocacy, or relationship-centered assistance.

The appeal of AI-enabled advising is clear: students may be able to receive timely responses to common questions, while advisors can devote more time to complex cases. But the distinction between routine and complex support is not always obvious at the outset of an interaction. Advising therefore presents a recurring institutional tension—AI may increase the speed and availability of routine support, while some of the value of advising lies in the human conversation that a routine question can make possible.

This concern is consistent with research emphasizing the importance of connection and coordination in the student experience. Bharadwaj et al. (2023) identify awareness, belonging, and coordination as important dimensions of student success, and Waldinger and Schulz (2023) synthesize evidence on the role of social relationships in long-term well-being. These sources do not establish that every advising interaction produces social capital or that automation necessarily weakens student connection. They do support the proposition that institutions should attend to the relational consequences of changing how students access support.

The key is ensuring that students can move easily from automated support to human judgment and relationship-centered assistance when they need it.

5.3 EQUITY, ACCESS, AND THE DESIGN OF STUDENT SUPPORT

AI may improve access for some students. As one participant noted, a tool that is available outside of business hours may be particularly valuable for students who work, care for family members, or have limited flexibility in their schedules. For these students, a timely answer to a routine question may prevent a delay or help them take the next step in an academic process.

Broad or even universal access, however, is not the same as equity. Students differ in their familiarity with institutional systems, confidence in asking for help, access to technology, and ability to assess the accuracy of automated information. Bailey et al. (2015) emphasize the importance of clear pathways and proactive guidance, particularly in institutions where students face complex choices and competing demands. AI-enabled support should be evaluated not only by the number of questions it answers but also by whether it helps students who are least able to navigate institutional processes on their own.

Institutions should consider whether their approach includes proactive human outreach, clear escalation paths, accessible design, and support for students who may not know when an automated answer is incomplete or when a more complex concern requires a conversation with a person.

5.4 DATA GOVERNANCE, ACCURACY, AND ACCOUNTABILITY

More advanced forms of AI-enabled advising may depend on integrating information across academic, financial, engagement, and student-support systems. That integration can create opportunities to identify students who may benefit from outreach, but it also raises significant questions about privacy, data quality, security, accuracy, and accountability.

One system-level leader described an initial interest in an AI system with direct access to student information systems, followed by concern about the implications of live data access, privacy, and institutional risk. The response was not to end experimentation but to continue testing in sandbox environments while maintaining clear limits on the use of live student data.

This example illustrates a broader governance principle: institutions should not assume that a tool's technical capability establishes an appropriate use case. Before deploying AI in advising, leaders should establish clear policies about what data may be used, who can access it, how recommendations will be reviewed, how errors will be identified and corrected, and when a student must be connected to a human advisor or other professional.

Data governance also includes questions of institutional autonomy. Institutions should understand how vendors handle student data, whether data are retained or used to improve external models, and what contractual protections are in place. These questions are especially consequential when tools interact with sensitive student information.

5.5 WHAT THIS MEANS FOR LEADERS

AI may help institutions expand access to routine support and reduce administrative burdens in advising. Its value will depend on whether it is implemented as part of a coherent student-success strategy rather than as a stand-alone technology solution.

Leaders should consider the following questions:

- What advising or student-support problem is the AI-enabled approach intended to address?
- Which questions or tasks can be handled reliably through automation, and which require human judgment?
- How will students move from automated support to an advisor or other professional when their needs are complex or urgent?
- What data are required?
- What privacy, security, accuracy, and accountability safeguards are in place?
- How will the institution assess whether the approach improves access, belonging, coordination, and student outcomes?
- Which students may benefit most, and which may face barriers or new risks?

Institutions should use AI to expand access to routine support—not to replace advising or reduce every student interaction to a transaction. Used appropriately, AI can make routine support more accessible while enabling advisors and other staff to focus on the work that depends most on human expertise, trust, advocacy, and connection.



SECTION 6: ASSESSMENT—DEMONSTRATING LEARNING IN AN AI-ENABLED ENVIRONMENT

Interview Perspective: A Detection Result Is Not a Finding of Fact

A campus technology leader described submitting writing he had produced himself to an AI-detection tool and receiving a result indicating, with 98 percent confidence, that the writing was AI-generated. The experience led him to question whether detection results could be treated as conclusive evidence in academic-integrity processes.

This example does not establish the accuracy or reliability of detection tools generally. It illustrates why institutions should be cautious about relying on a detection result alone when making judgments about student authorship or academic misconduct.

Generative AI is prompting institutions to reconsider how they assess student learning, communicate expectations for AI use, and uphold academic integrity. These questions are difficult because AI can support learning, feedback, and revision while also making it easier for students to submit work that does not reflect their own understanding or skill.

The challenge is not limited to detecting whether AI was used; it also includes determining what students should know and be able to do, how they should demonstrate that learning, and when AI use is consistent with the purpose of an assignment. The answers will vary by discipline, course level, learning objective, and institutional context. They will also require faculty time, professional development, and clear institutional expectations.

6.1 THE LIMITS OF DETECTION AS AN INSTITUTIONAL RESPONSE

Interviewees consistently expressed concern about relying on AI-detection tools as the primary response to questions about academic integrity. One educational technology scholar described the assessment challenge as difficult and emphasized the need for substantial faculty development if institutions are to use approaches such as oral presentations or other forms of direct demonstration effectively.

Other interviewees connected the issue to assessment design. A national foundation leader observed that many existing assignments can be completed using widely available AI tools. The implication is not that all conventional assignments have lost value. Rather, institutions may need to consider whether a given assignment provides sufficient evidence of the learning it is intended to assess.

As noted earlier in section 3.4, concerns about authorship and academic integrity long predate generative AI (Noble, 1998; Simmons, 1999). The emergence of generative AI has brought renewed attention to longstanding debates about how academic work is produced, attributed, and evaluated, while also complicating how these issues are understood and addressed in practice.

These sources provide historical context, even though contemporary institutions must answer different questions about generative AI. They nevertheless reinforce a familiar lesson: technology can change the conditions under which academic work is produced, but institutions still need clear expectations, sound assessment design, and educational approaches that support academic integrity.

6.2 EMERGING APPROACHES TO ASSESSMENT

The institutional question is shifting from “Can we detect AI use?” to “What forms of evidence would allow students to demonstrate the learning an assignment is intended to assess?” Interviewees described several approaches that institutions and faculty are beginning to explore. These approaches are not mutually exclusive, and none should be treated as a universal solution.

Transparent and disclosed AI use. One assessment leader described treating AI use as part of the learning environment rather than assuming it must always be prohibited. In this approach, students may be asked to disclose how they used AI, examine or annotate AI-generated material, or use AI as part of an assignment that evaluates their reasoning and judgment. The instructor retains responsibility for determining when AI use is appropriate and how it relates to the course’s learning goals.

Assessment redesign. Multiple interviewees emphasized moving beyond a sole focus on final products toward approaches that provide more evidence of process and understanding. These may include project-based work, oral presentations or examinations, portfolios, staged drafts, reflective writing, and other opportunities for students to explain their reasoning. A teaching and learning leader described organizing faculty support around learning goals rather than specific tools, recognizing that tools may change more quickly than the underlying principles of effective teaching and assessment.

One interviewee described an example from an institution in which AI-generated assessment variants were tied to a skills taxonomy derived from course descriptions, with the aim of giving students distinct assessments that measure comparable competencies. Institutions considering similar approaches should evaluate validity, accessibility, security, and alignment with learning outcomes in their own contexts.

Competency demonstration and remediation. A community college president described an approach in which concerns about extensive AI use prompt an opportunity for the student to demonstrate competency through rewriting, oral explanation, or another form of assessment rather than an automatic punitive response. This approach treats the immediate concern as a question about demonstrated learning. It may be especially useful where the institution’s goal is to identify gaps and support students in developing the relevant knowledge or skill.

Each approach requires careful implementation. Oral or project-based assessments, for example, can be valuable but may be difficult to scale in large classes without appropriate faculty support and workload consideration. Portfolio and process-based approaches may require new rubrics, revised course design, and clarity about what constitutes acceptable AI assistance.

6.3 FACULTY CAPACITY AND THE PACE OF CHANGE

The pace of generative AI adoption creates pressure for faculty to make assessment decisions quickly. Yet assessment redesign is not a simple technical adjustment. It requires instructors to clarify learning outcomes, determine which knowledge and skills students should demonstrate independently, and decide when AI use can be transparently incorporated into the learning process.

This work takes time. It also requires access to professional development, examples from relevant disciplines, opportunities to learn from peers, and support for redesigning courses and assignments. As an interviewee emphasized, faculty support is most durable when it begins with learning goals and instructional practice rather than with a single tool.

Institutional leaders should also recognize that expectations may need to differ across disciplines. The appropriate role of AI in a writing-intensive course, a clinical program, a laboratory course, or a course focused on foundational

quantitative skills may not be the same. A consistent institutional approach does not require identical assignments or identical rules in every course. It does require clear processes through which faculty can make informed decisions and students can understand the expectations that apply to them.

Assessment redesign should not become an unfunded expectation placed on individual instructors. Revising assignments and course practices requires time, resources, and institutional support, which may be less accessible to adjunct faculty and others with limited authority or compensated time for course development. Institutions should therefore treat assessment redesign as a shared responsibility and provide faculty with the support needed to undertake it effectively.

6.4 TRANSPARENCY, FACULTY AUTONOMY, AND INSTITUTIONAL COHERENCE

Interviewees described inconsistent course-level AI policies as a source of confusion for students. A campus technology leader described a faculty senate resolution requiring instructors to include an AI use statement in their syllabi. The policy did not require every instructor to take the same position on AI; it established a minimum expectation that students would know what was permitted, prohibited, or required in each course.

An assessment leader similarly described inconsistent expectations across courses as a source of student uncertainty. This raises a broader question about where AI policy should sit within an institution:

- What requires institution-wide consistency?
- What is better determined at the school, department, program, or course level?

Faculty autonomy is a core feature of academic practice, particularly in decisions about pedagogy and assessment. At the same time, institutions have an interest in ensuring that students receive clear, accessible, and consistent information about academic expectations. One possible approach is to establish minimum expectations for transparency while allowing faculty to decide how AI use aligns with their disciplinary standards and learning goals.

6.5 METACOGNITION, AI LITERACY, AND WHAT STUDENTS NEED TO LEARN

Generative AI also raises questions about the competencies students will need to develop. Metacognition—the ability to reflect on and regulate one’s own thinking—has long been an important concept in learning science (Flavell 1976). In an AI-enabled environment, students may also need to learn how to decide when to work independently, when to use AI, how to evaluate AI-generated output, and how to integrate that output responsibly into their own work.

Ayodele et al. (2026) describe an Augmented Cognition Framework that distinguishes between individual cognition and distributed work across a human-AI system. The framework offers one way to consider whether AI is supporting learning or substituting for the cognitive work an assignment is intended to develop. Related research emphasizes the role of metacognitive strategies in helping students critically evaluate, verify, and refine AI-generated outputs rather than accepting them uncritically (Dai 2026).

These perspectives do not mean that every course should assess AI use in the same way. They do suggest that AI literacy may become an increasingly relevant component of student learning. Institutions may need to help students develop the ability to use AI critically, recognize its limitations, verify information, and remain accountable for the work they submit.

6.6 WHAT THIS MEANS FOR LEADERS

The assessment challenge cannot be resolved through a single tool or policy. Institutions will need approaches that are aligned with their educational missions, disciplinary contexts, and student populations.

Leaders should consider the following questions:

- What knowledge, skills, and forms of judgment should students demonstrate independently in this program or course?
- When can AI use support learning, and when might it undermine the purpose of an assignment?

- What assessment approaches provide credible evidence of student learning in an AI-enabled environment?
- What support do faculty need to redesign assessments, communicate expectations, and respond to concerns about AI use?
- What minimum expectations for transparency should apply across courses?
- How will the institution help students develop critical AI literacy, including the ability to evaluate and appropriately use AI-generated output?

The goal is to ensure that assessment continues to provide meaningful evidence of learning while preparing students to exercise judgment in environments where AI is increasingly available.



SECTION 7: SYNTHESIS—WHAT THE USE CASES REVEAL TOGETHER

The preceding sections examine personalized learning, advising and student success, and assessment as distinct areas of institutional activity. These areas show that the central challenge is not selecting an AI tool for a particular use case; it is determining whether an AI-enabled practice advances institutional mission while protecting the human judgment, relationships, and learning processes on which higher education depends.

Across the use cases, the same tensions recur. Institutions seek to expand support without isolating students; increase efficiency without weakening trust or access to human help; create coherence without erasing faculty expertise; and act with appropriate urgency without treating experimentation as a substitute for governance. These are not problems that technology can solve; they are leadership questions that require institutions to make values-based choices and evaluate their consequences.

As one campus technology leader cautioned, institutions should consider how their choices about data and procurement may affect their long-term agency and control over institutional information. This concern applies across all three use cases. AI systems that support learning, advising, or assessment may depend on data, platforms, and vendor relationships that require careful institutional oversight.

7.1 INFRASTRUCTURE AND GOVERNANCE ARE FOUNDATIONAL

The use cases discussed in this paper share common infrastructure needs. Personalized learning depends on access to course materials, learning activity, and student-progress information. AI-enabled advising depends on accurate information from student information and support systems. Assessment tools require clear policies, secure environments, and processes for reviewing outputs and responding to concerns.

Interviewees described fragmented systems, data integration, and governance as significant constraints. One technology leader referred to the complexity of legacy systems as a “spaghetti ball.” Another described an AI platform that could not move into production use until governance frameworks, interoperability standards, and safeguards for student information were more fully developed.

These examples do not mean that every institution must build a fully integrated enterprise AI environment before using any AI tool. They do suggest that institutions should distinguish between low-risk experimentation and applications that depend on sensitive student data or consequential decisions. As the scope and stakes of an AI use case increase, so do the importance of data quality, privacy, security, accessibility, interoperability, and clear accountability.

Institutional capacity also varies. Some colleges and universities have more resources to invest in data systems, staff expertise, and vendor review than others. Leaders should therefore consider whether AI adoption could widen differences in institutional capacity and whether collaboration, shared services, system-level coordination, or targeted investment could help address those gaps.

7.2 FACULTY AND STAFF CAPACITY SHAPE IMPLEMENTATION

Across the three use cases, faculty and staff play a central role in determining whether AI use supports institutional goals. Faculty make decisions about course design, instructional practice, assessment, and appropriate expectations for student use of AI. Advisors, student-support professionals, instructional designers, technology leaders, and others contribute expertise that is necessary for responsible implementation.

Interviewees described several approaches to building capacity. A system-level leader emphasized discipline-specific communities of practice and the importance of including skeptical faculty in institutional conversations. A campus technology leader described similar efforts to support faculty learning and engagement. A community college president described pre-built course shells and teaching guides intended to help instructors, including new adjunct faculty, use AI-supported tools within an established instructional structure.

These examples suggest that faculty and staff development should not be treated as a one-time training event. AI tools, institutional policies, and disciplinary practices will continue to change. Institutions may need sustained opportunities for faculty and staff to examine how AI relates to learning goals, professional responsibilities, student needs, and disciplinary standards.

This work also requires attention to workload and support. Faculty and staff cannot be expected to redesign courses, assessments, advising practices, or data processes without time, resources, and appropriate institutional support. As one teaching and learning leader emphasized, AI-related professional learning should be connected to established principles of effective teaching and learning rather than focused only on the features of a particular tool.

7.3 EQUITY MUST BE CONSIDERED IN DESIGN AND IMPLEMENTATION

AI may create opportunities to expand access to learning support, routine information, feedback, and other services. Interviewees described examples of AI-enabled tutoring, culturally contextualized learning activities, and support available outside traditional business hours. These examples point to possible benefits, particularly for students who may have limited access to traditional forms of support.

At the same time, the benefits of AI will not be distributed automatically. Institutions differ in resources, technology infrastructure, staffing, and readiness. Students also differ in access to technology, familiarity with institutional systems, confidence in seeking help, and ability to evaluate automated information. Interviewees raised concerns about uneven institutional capacity, assumptions that access alone produces equity, and the need to consider data ownership and sovereignty in tribal college contexts.

The extent to which AI is equitable or inequitable is not inherent to the technology but manifests in how a particular use is designed, implemented, and evaluated. Institutions should assess who is likely to benefit from an AI-enabled practice, who may encounter barriers or new risks, and what additional support is needed to ensure that the initiative advances rather than undermines equitable outcomes.

Equity should be considered throughout the life of an initiative—when identifying a problem, selecting or developing a tool, determining what data may be used, piloting the approach, evaluating results, and deciding whether to scale it.

7.4 EVALUATING AI IN RELATION TO MISSION

Financial considerations are important in AI adoption decisions. Institutions need to consider costs, staffing, infrastructure, procurement, and the potential operational effects of new tools. Financial measures alone, however, do not capture whether an AI initiative advances the purposes of a mission-driven institution.

Brown (2026) proposes “return on mission” as a framework for evaluating AI initiatives beyond financial return. Applied in higher education, this approach asks whether a tool contributes to the educational and institutional outcomes the institution seeks to achieve. For example:

- Does the initiative support student learning, persistence, or access to appropriate services?
- Does it serve the students and communities the institution exists to serve?

- Does it support faculty and staff in carrying out their responsibilities?
- Does it protect privacy, accessibility, equity, and institutional autonomy?
- Does it strengthen or weaken the relationships and learning processes that are central to the academic mission?

A mission-based approach also requires institutions to establish measures of success before implementation. For an AI program pilot, these measures might include student learning, access to support, quality of feedback, staff workload, equity of outcomes, privacy and security performance, or student and faculty experience. Institutions should use the results to refine an initiative, determine whether it is ready to scale, or decide that it should not continue.

The Augmented Cognition Framework described by Ayodele et al. (2026) offers a complementary lens. The framework distinguishes between individual cognitive work and work distributed across a human-AI system. In the context of this paper, it can help leaders ask whether AI is supporting students and professionals in developing judgment or substituting for the cognitive work that learning and professional practice require.

In personalized learning, this may mean asking whether AI supports practice, feedback, and productive engagement. In advising, it may mean asking whether AI supports staff judgment and creates appropriate pathways to human assistance. In assessment, it may mean asking whether students can demonstrate both disciplinary knowledge and the ability to use AI critically and responsibly.

7.5 SHARED LEADERSHIP QUESTIONS

Across all three use cases, the most important questions are about what AI use will mean for students, faculty, staff, and the institution's mission.

Institutions will need to make context-specific decisions. They can begin by asking:

- What problem is this initiative intended to address?
- What outcomes would indicate that it is advancing institutional mission?
- What infrastructure, governance, and human capacity are required?
- Who is likely to benefit, and who may face barriers or new risks?
- What human judgment, relationships, and learning processes must remain central?
- What evidence will determine whether the institution should revise, scale, or discontinue the initiative?

These questions do not eliminate the uncertainty surrounding AI. They provide a common framework for making decisions that are evidence-informed, mission-aligned, and accountable to students and communities.



SECTION 8: LEADERSHIP, SHARED GOVERNANCE, AND INSTITUTIONAL COORDINATION

Throughout this paper, the focus has been on the leadership questions surrounding AI rather than the technology itself. The same principle applies to data infrastructure. As institutions expand their use of AI, shared infrastructure may become more important, but decisions about infrastructure should follow decisions about mission, governance, learner outcomes, institutional capacity, and trust. Those institutional decisions provide the foundation for determining what infrastructure is needed and how it should be developed.

Generative AI raises questions that extend beyond any single office or function. Its use now influences teaching and learning, assessment, student support, data governance, procurement, workforce practices, institutional finances, and public trust. For that reason, AI strategy requires both shared governance and sustained senior leadership advocacy.

The goal is not to centralize every decision about AI; faculty, staff, students, technology leaders, and other institutional stakeholders bring expertise that is essential to responsible implementation. But shared responsibility does not eliminate accountability for leaders; presidents and other senior leaders are uniquely positioned to align AI-related decisions with institutional mission, budgeting, risk management, governance, and strategic planning.

Without that sponsorship, institutions risk treating AI primarily as a procurement issue, leaving consequential decisions to individual departments, or expecting faculty and staff—often with limited time or support—to establish policies and practices on their own. The leadership task is to establish institutional purpose, provide resources and safeguards, and create conditions in which shared governance can function effectively.

8.1 AI INTERSECTS WITH EXISTING INSTITUTIONAL PRIORITIES

The ACE [2025 Fall Term Pulse Point Survey](#) indicates that senior leaders have high levels of concern about public perceptions of the value of college, student mental health, academic freedom and institutional autonomy, long-term financial viability, and enrollment. AI does not replace these priorities. It intersects with them.

For example, AI-related decisions may raise questions about faculty authority over course content, pedagogy, and assessment. They may require new investments in data infrastructure, cybersecurity, professional development, and vendor review at a time of financial constraint. They may also shape how students, families, employers, and the public understand the value of higher education and the meaning of academic work.

AI also affects student experience and well-being. Stephenson and Armstrong (2026) report that students describe varied effects of generative AI on loneliness, with similar shares reporting that AI makes them feel lonelier or less lonely. This finding does not establish that AI causes either outcome. It does indicate that institutions should consider how students experience AI, including when AI tools are used for support, companionship, or information. Research

on social connection underscores the importance of relationships to well-being (Pei and Zaki 2025; Waldinger and Schulz 2023).

These intersections do not mean that AI is the institution's only or most urgent priority. They mean that AI-related choices should be considered within the institution's broader strategic agenda rather than in isolation.

8.2 WHY SENIOR LEADERSHIP SPONSORSHIP MATTERS

Interviewees from different roles emphasized the importance of institutional coordination. One scholar of educational technology argued that AI strategy should not be treated as a responsibility of the IT organization alone. A vice president for research expressed concern that institutions may engage in extensive discussion about AI without establishing clear processes for making decisions. A teaching and learning leader observed that proposals for AI-related work are more likely to receive sustained attention when they are connected to institutional priorities and measures of success. These perspectives suggest that AI strategy requires both leadership sponsorship and shared responsibility. No single office is likely to have the authority or expertise to address every relevant question.

Technology leaders can assess systems, data, cybersecurity, and implementation requirements. Faculty and academic leaders can guide decisions about pedagogy, assessment, and academic standards. Student-support professionals can identify implications for advising and student experience. Legal, privacy, procurement, accessibility, and risk-management professionals can help establish appropriate safeguards. Students can provide essential insight into how AI is being used and experienced. Senior leaders, including presidents, can help align these perspectives around institutional missions and ensure that AI-related work is connected to governance, budgeting, accountability, and strategic planning.

8.3 ELEMENTS OF EFFECTIVE INSTITUTIONAL LEADERSHIP

The interviews provided examples of approaches that may encourage coordinated institutional action. These examples are not a universal model; institutions will need to adapt them to their missions, resources, and governance structures.

Listen and establish a shared understanding. One campus technology leader described surveying more than 7,000 members of the campus community before developing policy, identifying substantial growth in reported student use of ChatGPT over a two-year period. Institutions may benefit from gathering information about how students, faculty, and staff are already using AI, what concerns they have, and where additional guidance is needed.

Create governance that can adapt. Interviewees described standing committees, faculty-senate resolutions, and other mechanisms intended to establish clear expectations while allowing policies and practices to evolve. A governance structure should clarify roles, decision rights, escalation paths, and processes for reviewing high-impact uses of AI.

Support experimentation with appropriate safeguards. One technology leader described a design-and-build approach that combines prototyping with deliberate deployment. The underlying principle is to match the level of oversight to the level of institutional risk. Low-risk experimentation can proceed with relatively limited oversight, while uses involving sensitive student data, consequential decisions, or broad institutional deployment require more rigorous review and accountability.

Connect investments to institutional priorities. Interviewees described framing investments in data infrastructure through cybersecurity, compliance, and institutional-risk considerations as well as through potential educational benefits. This approach can help boards and other stakeholders understand why AI-related capacity may be necessary, even when the immediate application is still emerging.

Strengthen institutional and sector capacity. A national foundation leader emphasized the potential value of collective approaches to vendor engagement and accountability. Institutions may benefit from sharing procurement practices, evaluation methods, and lessons from pilots, particularly where individual institutions have limited negotiating capacity.

8.4 RISKS OF FRAGMENTED RESPONSIBILITY

The interviews identified several risks when AI-related work is fragmented across offices, departments, or individual instructors without sufficient coordination.

First, faculty and staff may be asked to make significant decisions about AI use without the time, professional development, or institutional guidance needed to do so. One interviewee raised particular concern about the burden this can place on adjunct faculty.

Second, when AI is treated primarily as a technology procurement question, institutions may focus on tool selection before defining the educational or strategic problem they are trying to address. Technology expertise is essential, but it is not sufficient to determine how AI should be used in teaching, advising, assessment, or other mission-centered work.

Third, decentralized adoption can make it difficult for institutions to understand what tools are in use, what data are being shared, and where risks may be emerging. One interviewee described discovering a large number of applications and AI-enabled integrations operating across an institution with limited central visibility. This example illustrates the importance of maintaining an inventory of high-impact tools and establishing processes for reviewing data use, accessibility, security, and vendor terms.

The appropriate response is not to prohibit all local experimentation; it is to provide a coherent institutional framework within which experimentation can occur responsibly and lessons can be shared.

8.5 MOVING FROM EXPLORATION TO COORDINATED ACTION

Students, faculty, and staff are already encountering and using generative AI. Recent student surveys indicate widespread use of generative AI among students, although reported rates and patterns vary by survey and context (Freeman 2025; Stephenson and Armstrong 2026). Institutions therefore need clear, adaptable approaches rather than assuming that AI use can be deferred until the technology is fully settled.

This does not require institutions to move quickly on every tool or use case. It does require them to establish the capacity to make informed decisions, support responsible pilots, evaluate results, and revise their approaches as technology and evidence evolve.

A coordinated approach can help institutions avoid two risks:

- Moving forward without adequate safeguards
- Allowing consequential practices to develop without shared expectations or accountability

As one assessment leader observed, institutions that do not develop their own approach may find that expectations are shaped primarily by vendors, student practices, or external pressures.

For senior leaders, the task is to ensure that AI-related decisions remain grounded in institutional missions. This includes asking what outcomes an initiative is intended to advance, what resources and safeguards it requires, who should participate in the decision, and what evidence will determine whether the institution should refine, scale, or discontinue the work.

Higher education leaders should not personally determine every AI policy or instructional practice. They should ensure that the institution has a coherent process for deciding what AI is for, where it belongs, what safeguards it requires, and how success will be judged. That responsibility cannot be outsourced.

CONCLUSION

Interview Perspective: AI in Service of Community Priorities

A two-year college is exploring AI-supported transcription as part of its work to preserve their tribal language that has a strong oral tradition. The institution is using recordings of fluent speakers to support transcription and is validating the results for accuracy. Decisions about whether and how to expand the work, including potential translation applications, are being guided by elders and other community leaders.

The example illustrates a mission-centered use of AI. Rather than treating the technology as an end in itself, the institution is considering how it may support cultural continuity and language preservation while maintaining community authority over the work.

The examples in this paper show that AI's value is not defined by technical capability alone. Its value depends on the purpose it serves, the people who guide its use, and the institutional and community context in which it is applied.

This paper has examined AI's implications for personalized learning, advising and student success, and assessment. Across these areas, the evidence and interviews point to several common considerations. Institutions need infrastructure and governance that are appropriate to the use cases they pursue. Faculty and staff need sustained support to make informed decisions about teaching, advising, assessment, and student support. Equity must be considered throughout the design, implementation, and evaluation of AI-enabled practices. And institutions should evaluate AI in relation to mission—not just cost, efficiency, or technical capability.

The interviews also underscore the importance of human judgment and relationships. AI may support feedback, access to information, routine services, and other forms of assistance. It does not remove the need for faculty expertise, advisor judgment, student agency, or meaningful connection among students, educators, and communities. Moss (2003) emphasizes that learning involves participation in social practices and communities. This perspective provides a useful reminder that institutions should evaluate AI not only by what it can produce but also by how its use affects the learning environments and relationships through which students develop knowledge, skills, and identity.

There is no single model for responsible AI adoption. Institutions differ in missions, resources, student populations, governance structures, technology infrastructure, and community relationships. A tribal college considering AI-supported language transcription will make different choices from a large university developing enterprise-scale AI systems. Those differences do not prevent shared learning; they make it more important for institutions to exchange evidence, implementation lessons, governance practices, and approaches to evaluation.

One community college president described the purpose of AI-related work as helping people develop the capacity to address future challenges for themselves. A tribal college president described a related aspiration: using technology in ways that “put humanity back in.” Together, these perspectives capture the leadership challenge. The task is neither to adopt AI for its own sake nor to wait for a universal playbook; it is to make deliberate, accountable choices about where AI can advance learning, student success, access, and institutional mission and where its use requires limits, safeguards, or a different approach.

Higher education's response to AI will not be defined by what the technology can do; it will be defined by the purposes institutions choose to serve, the people they include in those choices, and the human relationships and public responsibilities they refuse to trade away.

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