Towards Driving Systemic Change in Higher Education with Generative AI: What Have We Learned Thus Far? [1]

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Abstract

This article explores the potential of generative artificial intelligence (genAI) to catalyse innovation in higher education, emphasizing the current state of adoption together with systemic changes needed for successful integration. Despite the historical slow adoption of technological innovations within Higher Education, the sudden emergence of genAI tools like ChatGPT has significantly challenged traditional teaching, learning, and assessment paradigms. Through a survey of early adopters and the introduction of a novel Capability Maturity Model, this study identifies key challenges and opportunities in embedding genAI, focusing on academic integrity, pedagogical innovation, and the evolving roles of faculty and students. Institutions are encouraged to foster a culture of experimentation and continuous learning, supported by a framework for adoption and use. The active involvement of students as stakeholders and co-creators in the adoption process is emphasized to realize potential benefits. We suggest that a balanced approach, combining top-down strategic leadership with grassroots initiatives, is critical to harnessing genAI's full potential in enhancing educational quality. The article contributes to the ongoing discourse on digital transformation in higher education by outlining actionable pathways for institutions navigating the complexities of integrating genAI tools.

Keywords: *higher education, generative AI, institutional strategy, technology adoption, capability maturity model, student involvement*

Challenges to Traditional HEI Innovation in T&L

When we consider technology innovation in higher education, such as the Personal Computer (PC) or the Internet and the World Wide Web (WWW) and the combination of the two together

1. The authors would like to thank the staff of the APRU Secretariat under the leadership of Prof. Thomas Schneider and acknowledge their help in distributing the survey to its members.

2. The authors have used genAI tools (ChatGPT, Claude) in this paper as follows: to categorize and summarize emerging themes in the free text responses in the surveys; to provide feedback on the manuscript using the editors' suggestions; to identify and summarize specific topics on the references; to create and import references from URLs to Microsoft Word; and, to create a chart of key survey results. All final decisions and content remain the authors' responsibility.

with ubiquitous mobile broadband connectivity, both technological progress and technology adoption have been slow taking many years to be adopted by most of the stakeholders in Higher Education Institutions (HEIs). Research has found that "the average time between adoption of an innovation by the first institution and its adoption by half of them was more than 25 years" (Siegfried, Getz, & Anderson, 1995).

Generative AI (hence genAI), along with the steam engine, the internal combustion engine, electrification, electric motors, as well as semiconductors, personal computers, and the Internet are examples of General Purpose Technologies (GPTs) which "are characterized by pervasiveness (they are used as inputs by many downstream sectors), inherent potential for technical improvements, and innovational complementarities, meaning that the productivity of R&D in downstream sectors increases as a consequence of innovation in the GPT" (Bresnahan & Trajtenberg, 1992). However, several factors suggest that genAI adoption will proceed faster than previous technologies. Unlike hardware-based innovations requiring significant capital investment, such as building electricity or railway networks, genAI rely on cloud infrastructure personal devices, such as laptops or smartphones and Internet connectivity that students and faculty already have at their disposal. This led to ChatGPT reaching 100 million monthly active users in just 2 months (CIO Daily Updates, 2023) which made it the fastest-growing consumer app.

Most critically, both faculty and students gained access simultaneously, removing the supply bottlenecks that historically slowed adoption. Current data supports this acceleration: 92% of UK undergraduates now use AI, and 86% of education organizations report the highest AI adoption rates among all industries (Josh Freeman, 2025). Students were also early Internet adopters (74% used internet 4+ hours/week by 2008) (Jones, Johnson–Yale, Millermaier, & Pérez, 2009), but institutional change remained slow as adoption alone is a necessary but not sufficient condition for systemic transformation.

Setting aside (but not underestimating the importance of) digital equity issues, most HEI stakeholders now have access to a personal computer, and access to email and the World Wide Web. The impact in teaching & learning has been in two broad domains: wide availability of *online multimedia teaching material* including high quality and free of charge ones, such as the ones offered by Massively Open Online Course (MOOC) platforms and *personal work productivity*, such as Word Processors, and email software clients. MOOCs introduced the promise of much expanded access to Higher Education; however, they have not been integrated in mainstream Teaching and Learning in HEIs, nor expanded access through hybrid education modes.

And while we moved from the blackboard to the overhead and/or slide projector and now to presentation software, such as PowerPoint and Learning Management Systems, the teaching process remains largely the same, the lecture and the presentation content, while assessment approaches have not substantially changed either.

Siegfried et al (ibid) attribute the slow adoption of technological innovation to HEIs being "insulated from many competitive pressures" and the "the academic tradition of collegial decision making". Systemic change in higher education refers to comprehensive transformations that affect the entire institution or system rather than just isolated programs or initiatives. Research indicates that "the system requires powerful reasons for change" (İpek & Karaman, 2021) and what is different now is that there are three key factors creating a perfect storm. First, widespread adoption by students, faculty and the workplace; second, disruption of the assessment process; and third, the student adoption of AI tools in the Teaching and Learning process. Recently, Anthropic introduced Claude for Education (Introducing Claude for Education, 2025) with Learning Mode that guides students' reasoning process rather than providing answers, while OpenAI introduced study mode (Introducing study mode, 2025) which guides students step-by-step.

While there have been longstanding barriers to innovation in higher education which paint the background context on the canvas of system change in HEIs, more recent events fill the foreground, notably the disruption to teaching and learning following the one caused by the global COVID-19 pandemic.

Prior context: What Brought Us Here

In November 2022, when ChatGPT (GPT3.5) became readily available for large-scale public use, HEIs were emerging from a period of significant change, challenge and disruption brought about by the global COVID-19 pandemic. Over a period lasting two or more academic years starting in March 2020, institutions were required to very rapidly adopt technological and pedagogical change at scale, with varying levels of preparedness and success. The initial “pivot” to emergency remote instruction was characterized by doing what was possible in very short timeframes to ensure continuity of learning for students. This was subsequently replaced by a period of largely, if not fully, online instruction and a direct transfer of existing methods to a new modality. Not only were new skills and proficiency in new tools for presentation, collaboration and discussion needed (such as Zoom and MS Teams), design, delivery and assessment of courses needed to be re-imagined in a modality far different from that for which most of them were originally designed.

Challenges were significant for both faculty and students and distributed unevenly across different groups. Learning support staff mobilized to offer pedagogical and technological support at a scale at which few of their units were resourced to offer. Studies of the impact on student learning indicated that online learning during the pandemic had both positive and negative effects on students’ learning experiences. On the one hand, it allowed for greater flexibility and autonomy, but on the other hand, it also led to feelings of isolation and disconnection from peers (Pokhrel & Chhetri, 2021). Learning achievement is not simply driven by cognitive processes but is also heavily influenced by affective components such as motivation, resilience, well-being and a sense of belonging. Similar studies of school students found that students' mental health and overall well-being declined significantly during the pandemic, which negatively impacted their academic performance. The study also highlighted the importance of social support from family and friends in maintaining students’ emotional resilience (Cortés-Albornoz, Ramírez-Guerrero, García-Guáqueta, Vélez-Van-Meerbeke, & Talero-Gutiérrez, 2023).

As HEIs emerged from the disruptions brought about by the pandemic, into a state of “new normal” for the sector, it is clear that the predominant lasting changes have been those of evolution, not revolution. Most institutions reverted to in-person instruction and assessments, with added blended or hybrid elements to capture some of the affordances of online. The changes, overall, can be characterized as “additions to” rather than significant “re-modelling of.” At the same time, there was a clear sense of a “long-tail effect” of COVID-19, whether evidenced through concerns around student engagement and participation or faculty appetite for further innovation and change. It was into this post-COVID environment that ChatGPT was released.

The Generative AI Disruption to HEIs

The release of OpenAI's ChatGPT in November 2022 catalysed adoption patterns unprecedented in higher education history. By 2025, 92% of UK undergraduates report using AI tools, with 88% incorporating genAI into assessments—a 26 percentage point increase within just twelve months (Josh Freeman, 2025). Multi-institutional research across 19 universities confirms this rapid integration, finding "experimentation with generative AI is widespread, from those who are responding to keep up with their students, to those who are genuinely excited about how AI might positively transform teaching, learning, and research" (Baytas & Ruediger, 2025).

Primary concerns from the academic community centred around the threats posed by these tools to the integrity of assessments, even though early indicators showed that students leveraged this much more broadly (Cu & Hochman, 2023). These initial concerns around academic integrity have generated wide-ranging debates around potential solutions to the problem, from more effective policing writing with detection tools, redesigning assessments to either mitigate or embrace the tools, and reconceptualizing what plagiarism actually is in a world where AI-capability is increasingly built into the majority of digital tools in widespread use. There is an ever-increasing number of tools claiming to be able to reliably and accurately detect AI-generated text, though many developer and vendor claims do not live up to close scrutiny (Weber-Wulff, et al., 2023) when rigorously tested, and are further undermined when simple obfuscation techniques are used. Thus, the early dialogue around developing use of genAI tools was framed negatively: issues of plagiarism, scope for rampant misconduct and the imperative for detection dominated the emerging discourse.

As an alternative approach to detection, assessment redesign is a call to action for HEIs to fundamentally consider how they construct the opportunities for students to demonstrate achievement and mastery of intended learning outcomes, whether that is through mitigating AI use, or ways to leverage genAI in assessment design. Institutional teaching and learning centres are focal points for sourcing, curating and disseminating how to put different approaches into practice (UBC, 2024). Finally, scholars working at the interface of “AI and AI”—artificial intelligence and how it relates to academic integrity—have suggested that we need a different conceptualization of what plagiarism actually means for writing in an age of artificial intelligence, where writing will increasingly be a human-AI hybrid (Eaton, 2021).

Many institutions formed working groups, committees or task forces to create institutional position statements, principles and guidelines around the balance of opportunity and risks. Collation and curation of these shows many key similarities (HESA, 2024). Key themes that are universally present include emphasizing the importance of academic honesty, pedagogical integrations, ethical use and the need for faculty and student training and support. Many institutions have supported innovation and pilot studies into ways to incorporate genAI tools into teaching and learning, capturing case studies of promising practice and experimentation. Our own involvement with the Association of Pacific Rim Universities (APRU) project to explore genAI’s impact on Higher Education is surfacing individual and institutional approaches. Bringing together 60 institutions from across the Pacific Rim region, it has also highlighted the importance of context and culture at many scales: regional / geographical, institutional and disciplinary.

Issues such as AI-generated misinformation, copyright infringement, and the potential for biased outputs have led to calls for more robust ethical guidelines and regulatory oversight. HEI academic governance and pedagogical innovation processes generally operate across much slower timescales than these advances. We return to this issue later in this article when we consider adoption pathways.

What is the genAI technology that we should be thinking about?

The pace of change in this space represents a significant challenge to HEIs. The past thirty months have seen significant enhancements across many dimensions. Looking forward to understanding the changes that will be coming, it is best to understand the progress that has been made and some of the issues that are under debate.

Since ChatGPT appeared in November 2022, there has been significant evolution in Large Language Model (LLM) technology. As of the time of writing, and with less than 3 years since LLMs came into the limelight, we now have LLMs offered by multiple technology vendors, which now differentiate themselves in terms of operational characteristics mainly on:

- Task Performance, as captured by several tests that have emerged, such as MMLU (Hendrycks, et al., 2021) or the LMSYS Chatbot Arena Leaderboard (Chat with Open Large Language Models, n.d.), (Chiang, et al., 2024), (BRACAI, 2024). GPT-3.5 scored approximately 70% on the MMLU, while the top 7 models now score between 83.7% and 88.7% (BRACAI, 2024)
- Multimodal Capability, to handle beyond text, images, video, speech (listening and talking), which expands user interaction modality beyond text and allowing a more seamless exchange.
- Multilingual Capability that allows communications across different languages.
- Size of context window**,** which refers to the amount of data that the LLM will take as input from the user to respond to a query. A large context window allows the user to have several documents as input. Gemini 1.5 Pro has a 2 million token context window that allows a complete collection of papers to be input to respond to a query.
- Latency and Throughput**:** the original models would produce output at a rate that was reminiscent of teletype machines, while now we have much faster output.
- Cost is a key factor to scale deployments organization wide to tens of thousands of students and faculty. Cost of closed source systems is measured as $/(million) tokens, while for hybrid infrastructure it is the cost of cloud computing infrastructure. Significant progress has been made there. As an example, "the cost per token of [OpenAI's] GPT-4o mini has dropped by 99% since text-davinci-003 … introduced in 2022" (OpenAI, 2024).

There are several other characteristics that we have seen progress and choice, including the number of parameters & model size, the hardware platform they run, whether they are open or closed source, etc. For current leaderboards, please refer to (Klu, Inc., 2024) and (Chat with Open Large Language Models, n.d.). The above characteristics are just a fraction of the overall metrics used to evaluate the capabilities of LLMs as described in (Nucci, n.d.), (Quinn & Lecker, 2024) and (Karzhev, 2024).

Where do we go from here? When looking ahead to plan, we should think about future capabilities, but what would these look like? Is the future better performance on the road to Artificial General Intelligence (AGI), but how much and how quickly? This is a subject which is hotly contested by researchers, with some arguing that performance scaling laws project that exponential change will continue and all we need during training is more computational power, bigger data sets and bigger models (Kaplan, et al., 2020). Others, however, dispute this inevitability of continuous exponential change arguing that we need different architectures to achieve AGI, or that scaling laws are not correlated with emergent capabilities of LLMs (Narayanan & Kapoor, 2024).

In a rapidly evolving technological landscape, doing nothing is not an option. Students and faculty are already using genAI tools regularly (Microsoft Education, 2024), and this trend will only continue as these technologies become more integrated into both education and the workforce. Half of the students surveyed are regular users of genAI (Shaw, et al., 2023) and will continue to use it when students transition to employment (Microsoft and LinkedIn, 2024). To harness the potential of genAI for positive change in higher education, institutions must take proactive steps.

It's essential to recognize that waiting for the technology to stabilize is also not feasible. Instead, institutions should focus on understanding current trends, experimenting with new tools, and preparing for continuous change. By doing so, they can better equip themselves to adapt to the fast pace of technological advancements.

One approach is to apply Strategic Foresight, as employed by the APRU's Working Group on genAI. APRU used this methodology to map long-term future scenarios for HEI with genAI being widely adopted which is outside the scope of the current paper and will be presented in a separate paper. To understand the technological changes, we scan the current state and look back at the progress since the introduction of ChatGPT. Future potential scenarios, not intended as definitive predictors of the future, but rather possible future paths, provide a basis for interrogation of what an institution would need to consider, stop doing, start doing and do differently if that future were desirable and/or considered likely. Exploring the implications of further progress in emergent properties of LLMs with scaling laws, or emerging trends, such as voice output and agentic AI, can be factored in as "early signals" into planning different scenarios for the genAI future and its impact on Teaching and Learning as part of the Strategic Foresight approach. The reality, of course, is that different future pathways emerge from different contexts and to some extent the choices that institutions make.

Student Involvement in HEI adoption

Students are key stakeholders in how HEIs adapt to and adopt genAI tools. They bring distinctive experience, a diversity of perspective and high motivation to engage with this topic. Students have been early adopters with an informal poll at Stanford showed that in the Fall Quarter 2022 (ChatGPT appeared in the last month of the academic term) the key use case of genAI was for brainstorming, outlining, and forming ideas, while help with assessment was a distant second use case (Cu & Hochman, 2023). Further studies have shown that the majority of students at the University of Michigan and University of Edinburgh are using genAI (Duraisamy, et al., 2023), (Ferguson, 2023). Furthermore, in a new poll conducted by Impact Research (Rosenbaum, 2024), 82% of US undergraduates use genAI at least once in a while, with 49% on a weekly basis.

Students' surveys are showing a positive attitude towards genAI. A survey of undergraduate and postgraduate students from various disciplines of six universities in Hong Kong showed that students have a positive attitude toward genAI technologies (Chan & Hu, 2023). Similar positive attitude and acceptance towards genAI was shown in a survey in Morocco (Ismail, Khalifa, Laddaoui, & Sefiyaoui, 2024).

The survey in Hong Kong indicated that students have a clear view of where genAI is useful to them primarily on personalized learning, writing and brainstorming and research. Students are demanding from their institutions more AI skills in conjunction with critical thinking (e.g. assessing trustworthiness) and understanding the impact on academic integrity (Attewell, 2024). Jisc, the UK's digital, data and technology agency focused on tertiary education, research and innovation, ran student discussion forums (Jisc, 2024) with over 200 students across colleges and universities to understand student/learner perceptions of genAI and changes with respect to a prior survey (Jisc, 2023). One of the key findings is that learners are increasingly seeing these tools as having the role of collaborative coach to support critical thinking and learning, rather than purely as "answer providers".

These themes are echoed in the results of a comprehensive survey of 4000 students across 16 countries (DEC, 2024). These results show high adoption (24% of respondents using tools on a daily basis) with information retrieval and summarizing being the most common use tasks. Interestingly, a significant fraction of students (approximately half) does not feel they have sufficient knowledge or skills with genAI tools, nor feel prepared for a workplace where such tools are present. There was strong agreement from students that their institutions should be providing more training and experimentation opportunities, both for them and their professors.

Prior to the release of ChatGPT, a study (Glass & Kang, 2020) showed an increasing number of students year by year up to roughly half of the class, who were answering questions through look-up. This group exhibited lower performance at exams than the group who did their homework to produce the answer. As genAI can do both based on the instructions it is provided and given its pervasiveness to students, it is important that we provide students with genAI tools—and the skills to use them effectively—that will help the long-term effectiveness of their study and not undermine it.

It is clear that students are familiar with genAI, understand its benefits, use cases (Webb, 2024), recognize the value to them in their current and future endeavours, and have a range of viewpoints and concerns. Students do not have the full pedagogical viewpoint as indicated by the aforementioned study, nor are they ignorant as to their learning and the application of genAI technology. We should treat students as equals in the teaching and learning process, and also possibly more tech savvy than the faculty. Students are not consumers of pedagogical methods but have agency as to how they learn and what they need, when presented with data driven viewpoints. Moreover, the unprecedented rate of change necessitates that we adopt a growth mindset, and we shift from "Professor-as-sole-source-of-knowledge" to embracing uncertainty and experimentation. This is a seismic change for Higher Education, but also an opportunity for Higher Education students to assume agency over their learning as active participants and collaborators in forming, developing, evaluating, and improving genAI initiatives and not simply involved just for satisfaction surveys after the fact. Moreover, institutions should actively be in dialogue with students to understand their expectations and concerns. Students should be a primary and active stakeholder in genAI adoption at HEIs, a point to which we return below.

Moving Beyond Principles: Pathways to Adoption & Competency Development

A large number of institutions have created and published principles or position statements to guide AI exploration and adoption, arising as outputs from initial periods of dialogue and exploration of tools' capabilities and challenges. Institutions are now engaged in the complex processes of enabling access to these tools, supporting literacy and competency development in their effective use in HE settings, and mitigating some of the known concerns and limitations. It is clear that these efforts need to be a mixture of top-down and bottom-up approaches: a clear institutional vision for how these tools are going to feature within the academic landscape (even if the tools themselves continue to evolve at pace), augmented by local experimentation that aligns with pedagogical practice within the disciplines. It will be imperative to recognize the autonomy of instructors in design of learning experiences for students, and the oversight of academic Departments in designing programs of study as a whole.

Top of mind in such considerations will be the need to ensure ethical use of such tools in educationally effective ways. Here, HEIs need not re-invent the wheel: several broad ethical frameworks for use of AI currently exist and can be used as organizing structures into which institutions plan their own strategies and actions. These include the UNESCO framework for ethical AI (UNESCO, 2023), OpenAI's usage guidelines (OpenAI, 2024), Microsoft's (Microsoft, n.d.) or Google's (Google, n.d.) Responsible AI principles. There is much common ground across all of these, and articulation of such a framework will enable building of trust amongst HEI stakeholders (including faculty, staff and students). Amongst HEI networks, Australia's TEQSA focuses on academic integrity and assessment (Helen Gniel, n.d.) and (TEQSA, n.d.) and UK's Russell Group has developed a set of principles (Russel Group, n.d.). These frameworks, or a synthesis of them, provided guard rails for how activities take shape.

Context and culture play critical roles in determining what institutions will choose to do and how they might go about implementing it. We would suggest that at a minimum, institutions need to provide three types of spaces: those in which to experiment, those in which to learn and those in which they listen. Experimentation needs environments and venues for real deployment in taught courses, with appropriate technical guidance, to learn what works and what does not, and why. A space for learning will build skills, confidence and digital literacies for effective use and early adopters can serve as focal points for further discussion and activity within their home academic units. Finally, listening to the needs, concerns and fears of stakeholders (faculty, staff and students) will ensure that institutions keep sight of current and emerging critical issues (as it is certain that new issues will emerge as we adopt and deploy these tools more broadly).

Operationally, deployment of these tools represents a very different implementation model than other educational technologies. This is not the traditional enterprise deployment of software (e.g. desktop services, email, etc.). Nor is it, we would argue, quite the same as installation of a new Learning Management System (LMS) which requires both technical and pedagogical support to realize benefits to learners. With genAI tools, there is an additional opportunity to build new tools on top of existing LLMs that support particular pedagogical goals an instructor may have. A current example is the technique of Retrieval-Augmented Generation (RAG). The core idea is to enhance the generative process by first retrieving relevant information from a specified knowledge base, then using that information as a guide for generating content. This approach can help mitigate some limitations of generative models, such as producing factually inaccurate or irrelevant responses. Supporting faculty in how to build, train and deploy these tools is critical, so that they can focus on the pedagogical purpose, and hopefully, effectiveness of the deployment.

Finally, in terms of pathways to adoption, we would advocate again for this being a critically important opportunity to consider students as partners in navigating the challenges and changes that these tools will bring, building on the broad body of literature around this as an approach to recognize students as active contributors of their own educational experiences, rather than passive recipients (Cook-Sather, Bovill, & Felten, 2014), (Healey, Flint, & Harrington, 2016). Student use of these tools and their perceptions around them is continuing to evolve and see the potential of these tools and their importance in their future careers and lives, yet at the same time are cognizant of exactly the same challenges that have been articulated by Faculty with regard to equity of access, ethical use, potential for bias etc. Their active inclusion in institutional approaches to embedding these tools in courses and curricula will bring a unique perspective and active engagement in creating an environment in which all students can realize the benefits genAI tools have to offer for their education.

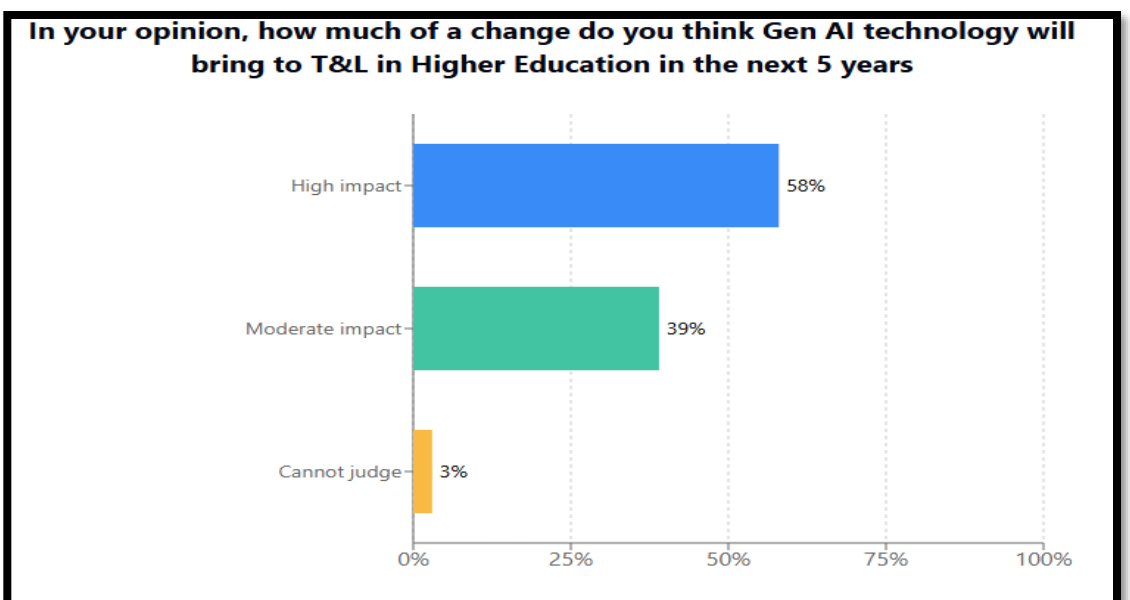
Perspectives from Early Adopters on Institutional Approaches

We sought insights from early adopters on how their respective institutions have approached genAI tools and their use, as well as their perspectives on what has worked and what needs to be improved. As part of our respective roles in the APRU project on the impact of Generative AI in Higher Education (APRU, 2023), we convened a two-day in-person workshop in June 2024, bringing together participants from across the 60 member institutions of APRU who had previously submitted case study examples of early innovation in the adoption of genAI tools in the HEI context. We collected 31 responses from 15 different APRU member institutions, in faculty and professional staff roles. Respondents completed an anonymous online survey, comprising a mixture of Likert-style questions and free text responses.

Our findings align with broader institutional research. Concurrent studies across 19 universities in the US and Canada found "familiarity and adoption levels among instructors and researchers are varied but rising," with widespread experimentation from faculty "responding to keep up with their students" to those "genuinely excited about how AI might positively transform teaching, learning, and research" (Baytas & Ruediger, 2025). This validates our survey's identification of institutional mobilization primarily at the exploration stage.

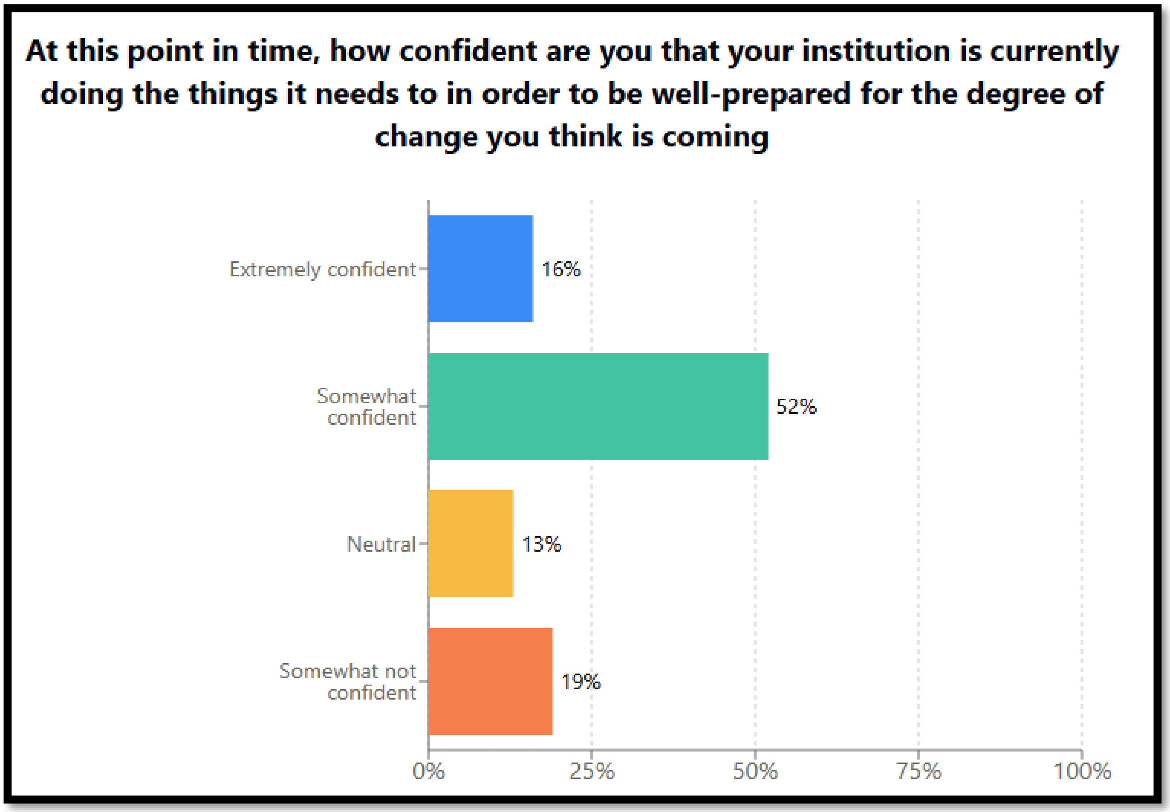
We present the key findings below. Participants being either early adopters or interested in genAI were naturally overwhelmingly bullish on its impact in HEI as shown on Figure 1 below.

Figure 1. *Assessment of GenAI Impact*



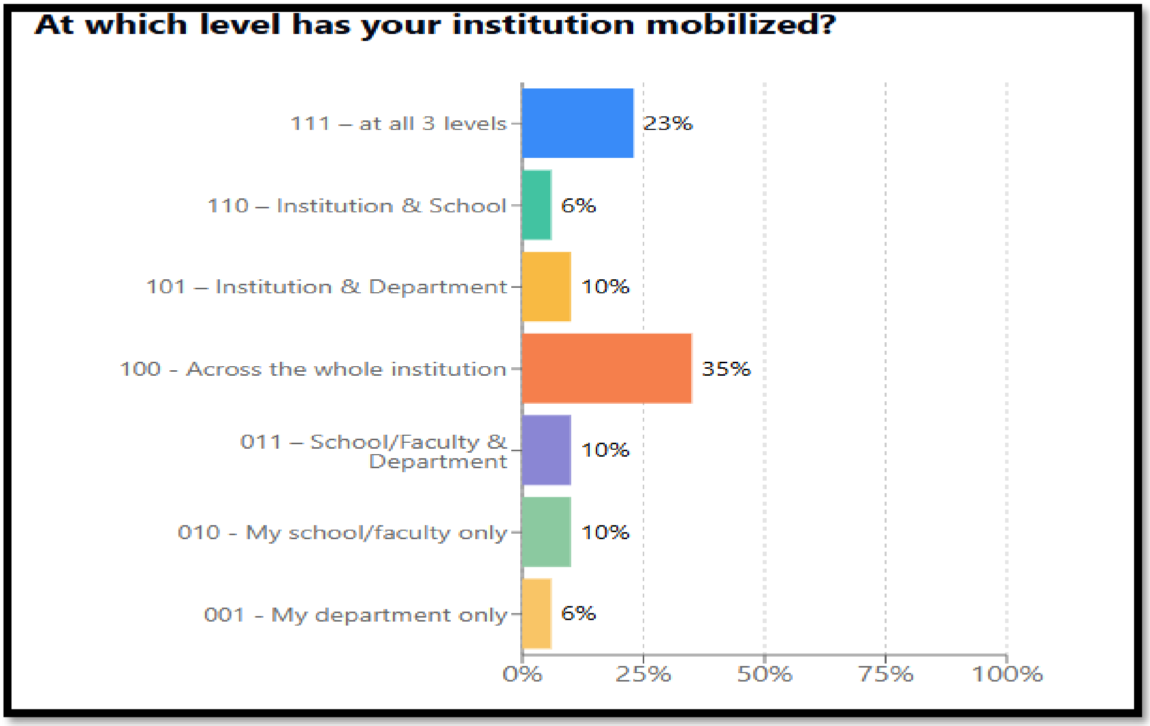
Evaluating how their institution is preparing, 2/3 of them feel positive about it. We will delve further into the positives and what can be improved further (32% are sceptical about the effectiveness) later on.

Figure 2. *Assessment of GenAI Institutional Preparedness*



We see though that the level of preparedness is still very uneven, with just ¼ happening across the institution, school/faculty and department, while 16% happening just at the school/faculty or department level. The key point is that genAI mobilization has not trickled down from the top and therefore it is a combination of top-down and bottom-up activities, confirming our earlier premise.

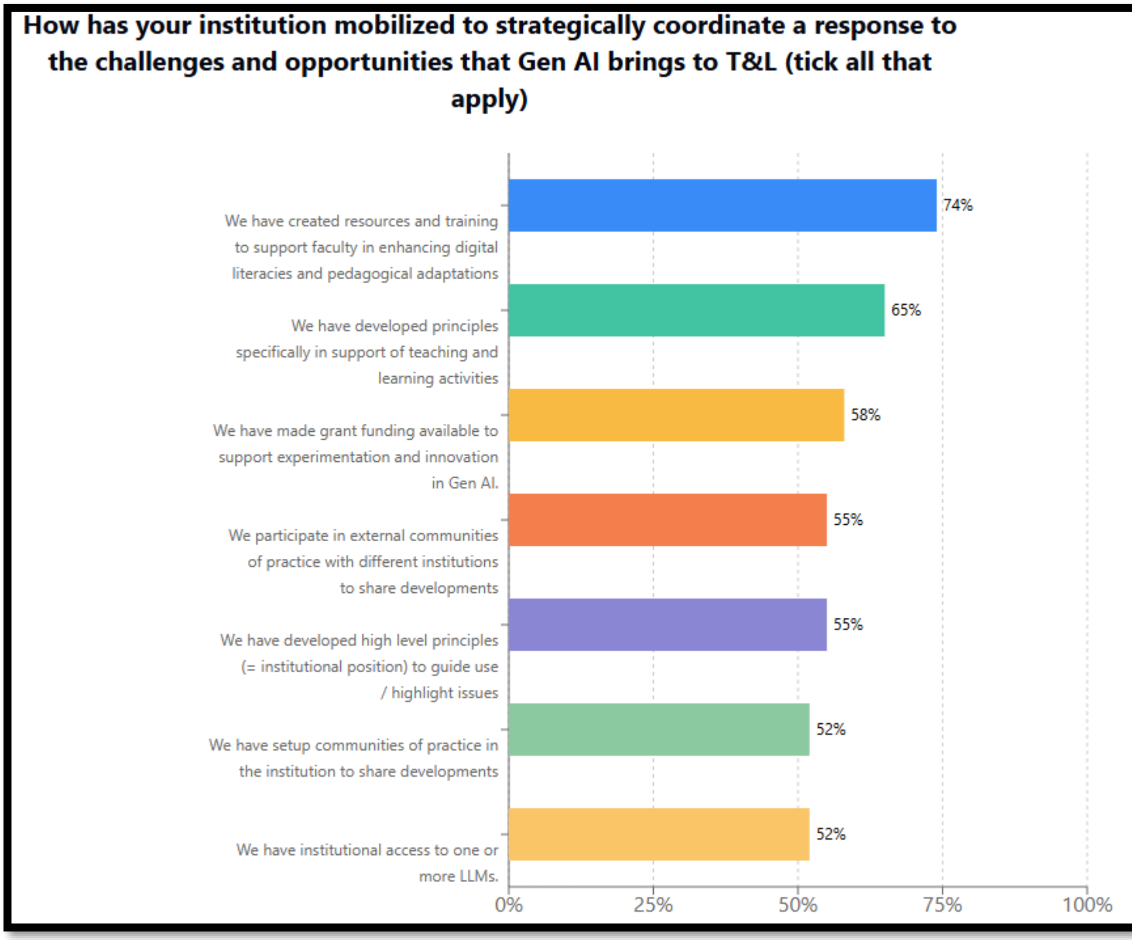
Figure 3. *Institution Mobilization Level (tick one)*



Looking with more granularity on what activities the institutions have undertaken, we see that these extend across three dimensions, providing *resources and support to faculty* (training, grant funding, access to LLMs), establishing *strategy and guidance* (both institutional principles and policies and specifically for teaching and learning) and thirdly, focusing on *community building, collaboration and practice sharing* (both internal and external communities of practice). Training is the most important activity, followed by guidance on how to apply genAI in the domain of teaching and learning through development of principles. These echo two of the three critical pillars of activities mentioned earlier in the paper (learning, listening) with less of a current focus on systematic experimentation.

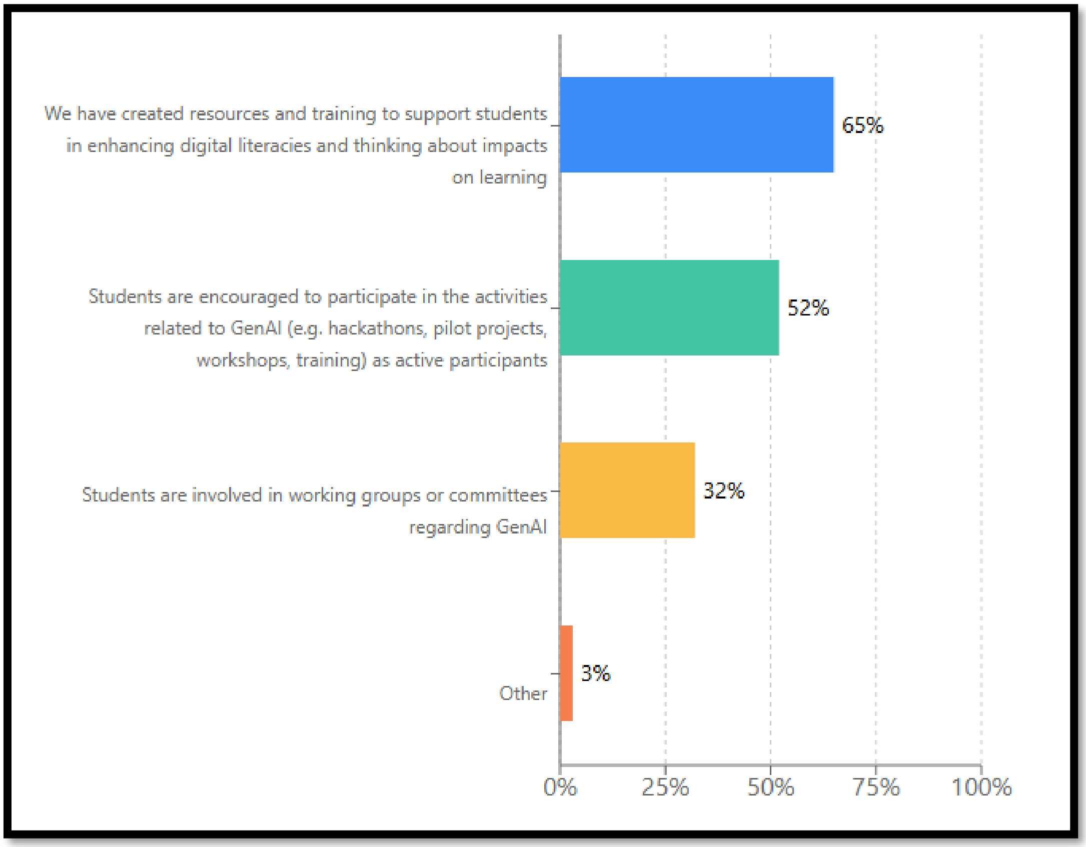
These three dimensions are the starting point for HEIs and as their practices maturity and capability evolve, we expect them to undertake additional activities, such as additional tools, hackathons, redesigning syllabus and assessments, etc.

Figure 4. *Institutional Activities (select key activities, tick all that apply)*



We examined earlier the critical role of student involvement in genAI, as they have a good understanding of genAI in higher education and expectations from their institutions. The good news is that institutions reach out to students to provide them with resources and support as well as pilot efforts. However, just 1/3 of the responses show that students are engaged pro-actively as key stakeholders in working groups or committees focusing on genAI. We regard that this reflects the maturity level of each institution, where at the first level student of experimentation it focuses on activities that are related to training, and other resources and participation in pilot projects, mostly as consumers of the use of genAI, while at a more advanced stage, they are involved pro-actively at shaping and developing the direction of genAI at their institution.

Figure 5. *How are students involved in this process? (tick all that apply)*



We asked participants to provide free text response questions about their impressions of what their institution was doing well and what they could / should be doing differently. An analysis of the text comments revealed the following commonalities of the top 3 themes:

Table 1. *What Institutions are doing Well and what they should Change or Prioritize More*

What institutions are doing well with Gen AI in T&L:	**What should your institution be doing differently or prioritize more of:**
Training and awareness	Training and skill development: need more!
Institutional support and leadership incl. development of policies	Curriculum impact assessment redesign and integration: do it rapidly
Openness to experimentation and integration, running pilots	Be more strategic on AI and provide more resources

The free text responses of what institutions are doing well are well aligned with the quantitative data, where the training, strategy and policies and collaboration and awareness are the right activities. In addition, the responses indicate that there is an element of *institutional culture that facilitates innovation and experimentation* which is important. This is distinct from strategy and guidelines.

The item on what HEIs should be doing differently or prioritize more provides some interesting insights. Respondents request more training and an elevation of genAI to a strategic pillar that as such requires further support. Moreover, after pilot project experimentation, we should move rapidly to understand the impact on curriculum and redesign it. This is consistent with our insights from the activities that HEIs undertake as they move along from the exploratory and experimentation phase to the production phase where genAI is used as a key tool in teaching and learning.

In a nutshell, the survey shows that early adopters assess that genAI will have impact on teaching and learning and that their institutions are doing the right things even though genAI has not permeated all the structures or levels of their institution. Early adopters focus on providing resources, such as training, developing policies and leadership to create a culture conducive to experimentation and innovation and establishing intra and inter-institutional collaboration. Moving to the next stage of scaling genAI across the institution will require even more training, elevating genAI to a strategic pillar, assess its impact on curriculum and assessment redesign and proactively engage students in the redesign process.

Issues in Scalability of Efforts in HEIs & Learnings from the Commercial Sector

While early adopters have made significant progress, scaling generative AI across higher education presents unique challenges. This section examines key factors for widespread genAI adoption, drawing insights from both the education sector and commercial world to identify strategies for overcoming barriers and progress using a capability maturity model.

To accelerate technological adoption, Siegfried et al (Siegfried, Getz, & Anderson, 1995) call for "governing boards need to explicitly encourage institutions to be more progressive, perhaps even identifying specific new practices that they want to see adopted." Ipek and Karaman (2021) identified five main themes: motivation, standards, structural change, whole school involvement and leadership and "highlighted the crucial role individuals play in the systemic change process".

Microsoft Asia and IDC Asia/Pacific conducted research on "Assessing APAC Education Sector's Use of AI" (Gnaneswaran, 2019) which showed that "the educational sector is [was] currently lagging in Data, Strategy and Investment, as well as Culture when compared to Asia Pacific's overall AI readiness".

In an interview with Prof. Jules White, Senior Advisor to the Chancellor on Generative AI & Professor of Computer Science at Vanderbilt University who is one of the pioneers of the adoption of genAI in higher education (White, 2024), he stressed the role of leadership to set the tone to instil a culture of experimenting and learning by allowing the use of genAI in the classroom, unless told otherwise and providing the funding to kickstart the project. White stressed the role of interdisciplinary collaboration called "our distinct culture of radical collaboration," by Vanderbilt's Chancellor Daniel Diermeier (Vanderbilt University School of Engineering, 2023).

We have also looked at lessons that can be obtained from the commercial world and that can be relevant to Higher Education. Recent research by BCG (BCG, 2024) and Microsoft and LinkedIn (Microsoft and LinkedIn, 2024) has shed light on effective strategies for genAI transformation within organizations. This transformation is not a simple technological upgrade but a comprehensive shift in how organizations operate and innovate.

This process requires a balanced approach, starting with top-down leadership making AI transformation a CEO imperative. Organizations need to spotlight AI champions who can demonstrate the technology's potential and inspire others to create a virtuous innovation circle.

Continuous training is crucial to keep pace with rapidly evolving AI technologies. However, the focus should extend beyond mere productivity gains to align AI initiatives with broader business strategies and value creation. Not just doing things faster but doing things more effectively to achieve the company's mission.

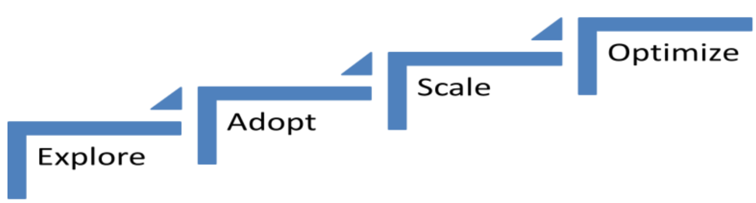
Effective implementation demands a holistic view of change management, including establishing clear OKRs (objectives and key results) to track progress. Equally important is a bottom-up approach that engages employees, exploring how AI and human workers can collaborate to enhance job satisfaction and outcomes.

Naturally, HEIs are not corporations led by a CEO who can mandate top-down initiatives and operationalize them using strategy, budget, etc. However, there are some key learnings that can be applicable to Higher Education. It starts with continuous training for all stakeholders (faculty, students). Leadership is key to establishing an innovation and experimentation culture and provides central direction and elevates genAI to a strategic transformation pillar. This transformation pillar should be tracked with KPIs and OKRs to ensure alignment. We should ensure that all stakeholders (incl. students) are engaged and promote intra and inter-institutional collaboration to share learnings. It will be important to prioritize AI initiatives that reinforce and accelerate the institution's mission.

In assessing genAI adoption, Papaspyridis (2024) has developed a holistic AI change plan that addresses the multifaceted challenges organizations face by recognizing that successful genAI implementation goes far beyond mere technological integration. At its core, the plan emphasizes the critical role of Strategy & Culture in driving AI transformation, ensuring that AI initiatives align with broader organizational goals and foster an innovation-supporting environment. Equally important is the establishment of robust AI Governance frameworks to guide ethical use and mitigate risks.

The plan also highlights the significance of People & Skills, acknowledging that upskilling and reskilling the workforce is crucial for leveraging AI's full potential. This human-centric approach is complemented by a focus on reengineering and optimizing structure & processes to support AI integration. In addition, Papaspyridis introduced a four-stage capability maturity model, that starts from an exploration phase of bottom-up pilot activities and training, continuing to a production phase supported by the development of appropriate policies and processes, then to the third stage of organization wide scaling of genAI and to the fourth and final stage where genAI shapes the organization's mission. This model is reflected and aligned to the survey findings, with most HEIs being at the pilot phase, with a few moving to the production phase which is supported by elevating genAI to a strategic pillar, assessing the impact on curriculum and assessment and proactively engaging students.

Figure 6. *AI Capability Maturity Model (c) Papaspyridis*



While technology remains a key component, it must be underpinned by strong data governance, ensuring high-quality, accessible and secure data. Finally, the allocation of appropriate resources, both financial and human, is spotlighted as essential for scalable AI adoption.

Learnings from the commercial sector can guide HEIs in scaling generative AI adoption, despite structural differences. Key factors include continuous training for all stakeholders, strong leadership to foster innovation and set strategic direction, and creating policies, processes, standards, a strong culture, and investment. Pilots are important to provide bottom-up innovation, with spotlight on these projects facilitated by collaboration and exchange of lessons learned.

We acknowledge that HEIs differ fundamentally from profit-driven enterprises both in terms of mission as well as structurally. Enterprises are top-down organizational structures where execution priorities, reviews and rewards are dictated by the CEO and the Leadership team. HEIs have looser structures with devolved decision making and faculty has significant autonomy. While enterprises focus on operational efficiency and revenue growth, HEIs have multifaceted and different missions while students do not constitute a uniform segment. Hence, transformation plans for for-profit enterprises and HEIs differ significantly and cannot be aligned. Our approach here is to signify commonalities between the two while considering nuances of HEIs, as indicated by the CRAFT framework which identifies Trust as one of the key pillars (Liu & Bates, 2025). Therefore, we have focused on comparing HEIs among themselves focusing on early adopters.

As organizations advance in their capability maturity, it is crucial to prioritize AI initiatives that reinforce the institution's mission and establish appropriate OKRs to track the transformation. A comprehensive change management plan addressing strategy, culture, governance, skills development, equity, responsible AI principles, academic freedom and integrity and evidence-based pedagogical changes, are essential for effective implementation and scaling of generative AI efforts in higher education. This necessitates slow but constant, reflective deliberation rather than the rapid “move fast and break things” mentality often celebrated in Silicon Valley. The more complex pathways should not constitute though an excuse for inertia.

Conclusions

This paper has presented an analysis of the context into which genAI tools emerged into widespread use in late 2022, together with an assessment of the current state of institutional preparedness and mobilization towards incorporating these tools into teaching and learning in Higher Education. We have surveyed “early adopters” of innovative use, which, although far from a representative sample of a faculty population, does give us additional insight into how institutions are approaching this issue and what more they might need to be thinking about. Parallels and learnings from the commercial sector are considered, through a four-stage Capability Maturity Model, while ensuring the differences and nuances of HEIs are considered. We can summarize our conclusions, supplemented with insights from the early-adopters survey, as follows:

AI Capability Maturity Model (CMM): we can frame the steps that HEIs take in their AI journey in terms of a four stage CMM. This allows a holistic approach in the change management across multiple directions, such as leadership and strategy, culture, processes and policies, resources, skills, curriculum, etc.

What early adopters think: they regard that genAI will impact significantly teaching and learning. Their institutions at the first exploration stage of the CMM, overwhelmingly mobilized at an institutional level, are providing training resources and awareness through collaborative sharing, are providing support including grant funding and establishing principles, both high-level and specifically in teaching and learning.

What can institutions do better: These are overwhelmingly positive first steps but transitioning to the second CMM stage of AI adoption, more training and skill development is needed as well as to elevate Gen AI to be a strategic pillar. Moreover, institutions should accelerate the deployment of Gen AI by assessing what will be needed to redesign the curriculum and resourcing it appropriately.

What advanced institutions do: at this AI adoption stage, HEIs undertake multiple activities, including conducting hackathons/rapid cycles of experimentation so they can test new ideas. In addition, they have a clearly articulated plan/approach for what they will do as an institution with respect to genAI for the near/medium term and get students to be involved in working groups or committees regarding genAI.

Students: At the initial explore CMM stage, students are well-engaged with AI tools and activities, both to support personal learning and discovery work, and in formal course assignments where this is permitted. In terms of strategic approaches, students are often included on committees or working groups, but it is not clear that they are active participants in the design of approaches as they are developed. In the faculty survey, one of the answers that stood out was from an institution that is "Encouraging a student-led AI-based project," which is notable as it empowers students to take an active role in using AI, preparing them for an AI-enabled workforce. Student involvement was identified in the improvement section of the survey where there was a call-out for more proactive involvement of students in the discussion, which we regard as a characteristic of the adoption phase of the CMM.

Figure 7. *AI Adoption Stages Using Papaspyridis CMM*

CMM Stage	Characteristics	Activities
1. Exploration	- Bottom-up limited scope pilots - Initial Awareness	- Provide training resources to faculty and students - Establish collaborative sharing - Offer grant funding - Create high-level principles
2. Production	- Strategic focus - Formal policies - Broader adoption in T&L	- Expanded training and resources - Conduct hackathons to identify use cases - Elevate genAI to strategic pillar - Create culture supporting innovation - Develop specific T&L policies - Assess curriculum & assessment impact
3. Scaling	- Organization-wide implementation across faculties and departments - Systemic changes	- Support rapid experimentation and data-driven educational insights - Involve students in working groups and committees on genAI in T&L redesign - Redesign curriculum and assessment - Establish clear transformation OKRs
4. Transforming	- genAI shapes institution's mission - Innovative use cases	- Integrate genAI into institutional mission - Redesign educational models - Lead industry collaborations - Pioneer new genAI applications

The early adopters in our survey have provided valuable insights, and it is now important to appreciate the broader challenge that lies in scaling these innovations across institutions. This transition from isolated initiatives to widespread adoption represents a significant hurdle. In the language of project management approaches, the fundamental challenge is to shift in approach from a waterfall model to an agile one: high flexibility and adaptability in an environment where the optimal solution will evolve and is not well-characterized at the outset, with frequent input from stakeholders to shape the path taken. Moreover, the rapid pace of innovation dictates an agile approach to adapt to the changes. Strategic foresight can help provide some preparedness for these changes.

Future Research

Further research can be extended to understand the perspectives of leaders in genAI, both short-term and long-term. Expanding the sample size of faculty respondents will allow also quantitative analysis of results as well as exploration of differences depending on HEI characteristics as well as disciplines. Resistance to change, transformation initiatives and their journey are additional directions to explore as well different perspectives influenced by national or cultural contexts.

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