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Generative AI Integration: Key Drivers and Factors Enhancing Productivity of Engineering Faculty and Students for Sustainable Education

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Abstract

Generative Artificial Intelligence (GAI) technologies are revolutionizing productivity and creativity across educational and engineering contexts. This study addresses a critical gap by examining the key factors influencing the successful integration of GAI tools to enhance faculty and student productivity, with a focus on higher education and its role in advancing sustainable development. Specifically, it investigates challenges, opportunities, and essential conditions for effective GAI adoption that support not only academic excellence but also the preparation of engineers capable of addressing global sustainability challenges in line with the United Nations Sustainable Development Goals (SDGs), particularly SDG 4 (Quality Education), SDG 9 (Industry, Innovation, and Infrastructure), and SDG 12 (Responsible Consumption and Production). A preliminary literature review identified significant factors requiring attention, further refined through interviews with 14 students and 13 faculty members, and expanded upon via a survey involving 54 students and 42 faculty members. Participants rated the significance of various factors on a five-point Likert scale, allowing for the calculation of the Relative Importance Index (RII). The findings reveal that while compliance with ethical standards and bias mitigation emerged as the most significant concerns, mid-level considerations such as institutional support, training, and explainability are critical for fostering GAI adoption in sustainable learning environments. Foundational elements, including robust technical infrastructure, data security, and scalability, are vital for long-term success and alignment with responsible and sustainable innovation. Notably, this study highlights a divergence in perspectives between faculty and students regarding GAI's impact on productivity, with faculty emphasizing ethical considerations and students focusing on efficiency gains. This study offers a comprehensive set of considerations and insights for guiding GAI integration in educational and engineering settings. It emphasizes the need for multidisciplinary collaboration, continuous training, and strong governance to balance innovation, responsibility, and sustainability. The findings advance theoretical understanding and provide practical insights for academia, policymakers, and technology developers aiming to harness GAI's full potential in fostering sustainable engineering education and development.

Keywords: Generative Artificial Intelligence (GAI); productivity; higher education; educational technology; Ethical AI; student and faculty perspectives; engineering education; Sustainable Development Goals (SDGs); sustainable engineering education

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1. Introduction

In the modern digital age, rapid technological developments are transforming our world like never before, reshaping the ways we live, work, and communicate with each other. From education to engineering, industries worldwide are experiencing profound transformations powered by digital innovations. These advancements not only boost productivity but also redefine the boundaries of creativity and intellectual exploration while also creating opportunities to align education and practice with the principles of sustainable development, particularly those outlined in the United Nations Sustainable Development Goals (SDGs). The emergence of modern technology is revolutionizing problem-solving, design, and efficiency, establishing unprecedented standards across all sectors. As businesses, educational institutions, and manufacturing firms navigate this dynamic landscape, they are compelled to adopt tools and strategies that align with rising demands for precision, adaptability, and innovation, which are essential qualities for maintaining competitiveness and relevance in a rapidly evolving market. Among these transformative tools, Generative Artificial Intelligence (GAI) is a pioneering force. Evolving from conceptual frameworks to powerful real-world applications, generative AI is revolutionizing industries by enabling unprecedented levels of creativity, efficiency, and problem-solving capabilities [1]. This technology not only enhances productivity but also serves as an enabler of sustainable practices by supporting resource efficiency, environmentally conscious design, and the development of future-ready engineering competencies. Unlike traditional digital tools that rely on predefined rules, GAI uses complex models to generate new data, images, or insights from existing information, providing an innovative way to increase productivity and creativity [2]. The key competency of generative AI is its ability to extract insights from existing information by using advanced computational models. This capacity to generate innovative outcomes has sparked great interest because of the potential to change established problem-solving approaches, expedite project designs, and increase productivity. Consequently, GAI is regarded as a technical milestone, delivering precision and adaptability in industries where accuracy, quality, and innovation are crucial. GAI adoption has grown across the public and private sectors worldwide as organizations seek to improve productivity and quality. According to recent research, more than 80% of companies use machine learning technology to improve products, with 65% focusing on process innovation and 54% on job automation [3]. This tendency mirrors the wider trend of using GAI to improve processes, automate repetitive operations, and spur creativity. However, the route for a successful GAI deployment is challenges [4]. Concerns about data privacy, model dependability, and the necessity of specialist skills continue to be key impediments to smooth adoption. As organizations integrate GAI, it symbolizes more than a tool for efficiency; it represents a transformative shift in utilizing technology to elevate productivity, improve decision-making, and expand creative capabilities [3].

GAI encompasses a diverse array of tools and platforms, such as ChatGPT, Intercom, Google Gemini, Botpress, Chatbot, Microsoft Copilot, Perplexity AI, Botsonic, and Claude [5]. These tools are engineered to produce content, solve problems, emulate human expertise, and foster an interactive and intuitive user experience. What sets GAI apart is its ability to seamlessly merge technical complexity with user accessibility, capturing widespread interest in both the public and professional spheres [6]. Initially adopted for personal applications, these tools quickly moved into professional environments, demonstrating their ability to enhance workplace efficiency, creativity, and collaboration [7]. This shift underscores the broader evolution of how productivity is perceived and optimized across industries. At its core, productivity can be categorized into three key dimensions: capital, material, and labor productivity [8]. Among these, labor productivity, the ability to

maximize the economic value generated through human effort, stands out as particularly relevant in the context of GAI adoption.

This research introduces the concept of educational productivity, defined as the degree to which individuals in academic settings, both faculty and students, achieve desired educational outcomes efficiently and with high quality. Conceptually, faculty productivity refers to the effective and efficient execution of academic tasks such as lesson preparation, assessment design and grading, supervision, and research dissemination, while sustaining pedagogical quality and student engagement. Student productivity denotes learners' capacity to complete academic assignments, design projects, and research tasks efficiently and with demonstrable understanding, creativity, and problem-solving ability. Operationally, this study assesses productivity through perceived improvements in (1) time efficiency (reduced effort and duration of routine tasks), (2) output quality (clarity, accuracy, and creativity of academic work), and (3) performance outcomes (achievement of learning or teaching goals). Within this framework, GAI technologies are viewed as catalysts that automate repetitive processes, facilitate personalized learning, and provide rapid feedback, thereby enhancing both faculty and student productivity in measurable and sustainable ways. However, despite its significant benefits, the use of generative AI in educational processes raises many problems when applied across various disciplines [9].

In this study, sustainability is interpreted primarily from an educational and institutional perspective, emphasizing the long-term capacity of academic systems to adapt, innovate, and maintain quality in the face of technological transformation. Within this framing, pedagogical sustainability refers to ensuring the continuity and resilience of learning and teaching processes, while institutional sustainability concerns the ability of universities to evolve their infrastructure, governance, and competencies to integrate GAI responsibly. Although environmental sustainability is not the central focus, the shift toward digital and data-driven solutions indirectly supports resource efficiency and the reduction in material waste. Accordingly, this study situates sustainability as a multidimensional concept linking pedagogical continuity, institutional adaptability, and responsible technological innovation.

Academic and engineering disciplines, in particular, benefit from the capabilities of GAI because of their reliance on complex data analysis and modelling, and the need for creativity and precision. In academia, GAI may adapt teaching materials, automate administrative processes, and assist academics with research endeavors [10]. In engineering, GAI may simplify project design, improve simulations, and automate regular but critical operations, such as data analysis and report preparation. However, implementing GAI in these fields presents unique challenges: academia must address data integrity and ethical management, whereas engineering demands rigorous standards for accuracy, safety, and regulatory compliance. At the same time, these challenges extend to ensuring that GAI is integrated responsibly into curricula to advance sustainable engineering education that balances productivity, ethics, and environmental responsibility. Despite GAI's promising applications of GAI, a substantial research gap remains regarding its specific impact on productivity within these disciplines [11,12]. While some studies highlight GAI's general potential, few have analyzed the nuanced factors affecting its effective integration, such as academia's data privacy needs and engineering's strict accuracy standards. Addressing this gap is essential to fully realize GAI's potential and to identify the factors that drive or hinder its successful implementation in academic and engineering environments.

Therefore, the primary objective of this study is to investigate the integration of Generative Artificial Intelligence (GAI) within the context of engineering education, with a focus on identifying and assessing the critical factors that influence its successful adoption and impact on educational productivity among engineering students and faculty. Another significant research gap addressed by this study is the limited understanding

of how GAI implementation can optimize productivity and performance within these specialized fields [12]. This study aims to bridge this gap by examining key challenges and proposing actionable strategies to enhance GAI's effectiveness, with direct relevance to Sustainable Development Goals such as SDG 4 (Quality Education), SDG 9 (Industry, Innovation, and Infrastructure), and SDG 12 (Responsible Consumption and Production). The outcomes of this study are expected to provide a ranked analysis of integration factors that address implementation barriers and maximize GAI's positive contributions to productivity, establishing a foundation for future GAI integration efforts in engineering education.

This study aims to address these gaps by investigating the following questions:

- RQ1: What challenges influence the utilization of GAI from the perspective of engineering students and faculty?
- RQ2: What are the key factors that affect the adoption of GAI to enhance productivity in engineering education?

This study makes both theoretical and practical contributions. On a theoretical level, it deepens our understanding of how GAI technologies can be strategically aligned with productivity goals in fields that require precision and strong ethical oversight [13]. From a practical standpoint, it offers actionable guidance for educators, learners, and other professionals on implementing GAI technologies effectively, with a focus on addressing critical issues such as data privacy, model reliability, and compliance with regulations [14]. The implications of this research extend beyond engineering education by contributing to the creation of sustainable learning environments that integrate innovation, productivity, and responsibility. By establishing a framework to examine GAI's influence on productivity, this study provides a versatile model that can be adapted to other high-stake areas, including healthcare, finance, and legal services. These insights may also benefit policymakers by supporting them in fostering responsible AI integration across diverse sectors.

2. Literature Review

This section reviews the current research on the application of GAI technology, with a particular focus on its transformative impact within engineering education. The integration of GAI into educational and engineering settings holds significant potential to reshape both established procedures and broader practices, offering powerful tools to enhance productivity, creativity, and problem-solving capabilities [15]. Building on existing studies, this review identifies key factors influencing the acceptance and successful adoption of GAI, explores associated challenges and opportunities, and proposes actionable strategies to support its effective and ethical implementation in engineering education contexts [16].

As tools, ChatGPT and similar systems are recognized for their ability to automate complicated processes, increase analytical precision, and boost productivity across academic and engineering sectors. In academia, GAI is redesigning educational delivery, streamlining research methodologies, and optimizing administrative operations [17]. In engineering, it involves reinventing design processes, increasing efficiency, and supporting sustainability initiatives. These advancements highlight the dual role of GAI in improving efficiency while fostering innovation and contributing to societal progress.

The relationship between academic and engineering contexts provides a unique opportunity to leverage insights from one discipline to enhance the integration of GAI into the other. For instance, the research-driven adaptability of academic institutions can inform iterative design and optimization in engineering, while engineering's emphasis on practical applications can guide the deployment of GAI tools in education and research [18]. Understanding these synergies is essential for maximizing the benefits of GAI technologies. Therefore, this review offers a comprehensive synthesis of current findings, distinguishing

GAI from previous technologies by its generative capabilities and potential to support creativity and adaptability. By focusing on ethical, technological, and social considerations, it highlights the importance of careful integration to fully realize GAI's potential across academic and engineering sectors.

2.1. Challenges of GAI Integration

This subsection investigates the major challenges to effective adoption as well as ways to overcome them. While ethical considerations, including algorithmic bias, data privacy, and system transparency, have been extensively highlighted in prior literature [19–21], additional challenges, such as technical limitations and integration issues, require deeper analysis.

One pressing concern is the technical challenge of integrating GAI systems with traditional electronic systems, which may lack the compatibility or infrastructure necessary for smooth operation. Advanced GAI algorithms often require high computational power and modern frameworks that may not be supported by legacy systems in academia or engineering firms [22]. For instance, integrating GAI into outdated engineering workflows can disrupt processes or result in inefficiencies if not carefully managed. Furthermore, challenges related to scalability in applying GAI solutions to larger datasets or multidisciplinary environments remain inadequately addressed [23]. These difficulties call into doubt the legitimacy and dependability of academic output, which are critical to institutions' instructional missions [24]. Furthermore, if GAI techniques become more widely employed in research, there is concern that they could reinforce existing data biases and perpetuate systemic disparities [25]. For example, biased algorithms may lead to exclusionary or destructive design solutions in engineering because they may ignore diverse user desires or environmental considerations, thereby compromising safety and efficiency [26,27]. Moreover, institutional resistance to GAI implementation remains a major obstacle. Many institutions are hesitant to use new technologies, owing to concerns about disrupting existing educational methods, fear of job displacement, or a perceived lack of technical knowledge [28]. Faculty and staff may perceive AI systems as rivals rather than aids for improvement, fueling mistrust and resistance [29]. To overcome this opposition, institutions need to build comprehensive change management methods that promote an understanding of the benefits of GAI, such as reduced administrative costs, more tailored educational experiences, and improved research capacities [30].

Another major hurdle is regulatory compliance, particularly in terms of data security and intellectual property problems [31]. Because GAI systems often require massive amounts of sensitive data, universities and engineering firms must manage the legal difficulties surrounding their use [32]. Institutions must ensure that the data utilized by AI models are safe and ethically sourced, and the usage of these tools must comply with data privacy rules, such as the General Data Privacy Regulation (GDPR) in Europe [33]. Although the regulatory environment is changing, institutions and businesses frequently lack clear standards due to gaps in existing policies, which creates confusion regarding the use of GAI tools [34]. Moreover, the lack of familiarity with GAI techniques is a major challenge [35]. Many researchers, engineers, and educators lack the knowledge necessary to comprehend the potential and constraints of new technologies completely [36]. Their capacity to evaluate the efficacy of GAI technologies and incorporate them into their processes is hampered by this knowledge gap. Encouraging stakeholders and guaranteeing the effective implementation of GAI requires thorough training programs and workshops based on the unique requirements of academic and technical experts [37].

2.2. Factors Influencing GAI Adoption

The effective integration of AI into academia and engineering is significantly influenced by several critical factors. These factors are essential to ensure that the value of GAI is realized in ways that foster innovation, increase operational efficiency, and ensure equity [38]. Academic integrity, potential for administrative automation, and individual learning capabilities influence academic institutions' use of GAI [39]. By customizing information to each student's specific needs, personalized learning powered by GAI has the potential to completely transform education and improve learning outcomes and student engagement [40]. A more inclusive approach is possible through these systems, which provide educational opportunities for students with a range of needs, including those from minority backgrounds or those who require accommodation for disabilities [41]. Furthermore, by facilitating the automation of time-consuming processes, such as data collection, literature review, and hypothesis development, GAI can elevate research [42]. GAI facilitates a more dynamic and productive research environment by freeing researchers to focus on higher-order tasks, such as data analysis and investigating new concepts [43].

The ability to improve the teaching effectiveness, data accessibility, and interpretability of AI are factors that influence faculty acceptance of GAI [44]. AI-powered solutions can automate administrative tasks such as scheduling, grading, and reporting instructors' time to devote to students and research initiatives [44,45]. Furthermore, techniques that assist in content creation, such as creating exam questions or summarizing research articles, can greatly reduce effort, allowing for more effective teaching and improving students' overall learning experiences [46]. Especially in disciplines like engineering that rely heavily on data-driven methods, the ability of Generative AI to generate insights and improve complex analyses could dramatically improve research productivity and accelerate scientific discovery [47,48].

Design optimization, cost reduction, and sustainability objectives are some of the factors that have a significant impact on GAI acceptability in the engineering sector [49]. For example, an AI-based generative design can generate many design possibilities based on specific attributes, such as material types, environmental conditions, and structural requirements, providing engineers with innovative and optimal solutions that they otherwise would not have found [50]. These designs allow for rapid testing and iterations, which can reduce the time and cost of engineering projects and enable rapid prototyping and development [51]. Furthermore, GAI is essential for advancing sustainability goals because it helps engineering students or engineers design more environmentally friendly and energy-efficient systems that reduce waste and improve resource use [52]. Multidisciplinary use of GAI is another crucial factor [52]. AI systems often draw on knowledge and techniques from various disciplines in both academic and engineering settings [52]. For example, concepts from physics, materials science, and computer science can be combined when using GAI in engineering designs. Because stakeholders from many backgrounds come together to address complex challenges such as climate change, renewable energy or urban planning, this multidisciplinary character fosters collaboration and creativity [47,53].

2.3. Opportunities for GAI in Academia and Engineering

GAI offers a wide range of options in both academic and technical settings, with the ability to dramatically enhance productivity, creativity, and efficiency. GAI offers academics the opportunity to improve individual learning experiences, adaptive learning systems, and the research process as a whole [54]. Students' learning paths are already more personalized because GAI-powered systems analyze their performance and development, adjust materials to fit their pace, and provide additional resources to help students [52]. Additionally, by allowing instructors to track student progress in real time, these technologies make

it easier to provide quick data-driven feedback that can guide subsequent instruction [55]. Furthermore, by automating the production of academic materials such as research summaries, test questions, and syllabi, GAI frees up faculty time so that they can focus more on mentoring and direct instruction, while also encouraging creative research. By automating data collection and analysis, GAI speeds up the discovery process in research and enables researchers to quickly find patterns and correlations in large datasets [56]. Researchers from many fields can easily exchange data and resources owing to these platforms, which can also support joint research initiatives [57]. The interdisciplinary properties of GAI will enable increased collaboration and integration of ideas across disciplines, as research challenges become more complex, potentially leading to discoveries that would not be feasible within traditional academic silos [58].

In fact, GAI provides significant opportunities for design innovation, operational effectiveness, and sustainability in the engineering field. For example, generative design algorithms may generate a large number of design options that meet certain requirements, thereby enabling engineers to quickly improve designs and investigate innovative solutions [59]. For industries such as aerospace and automotive, which rely on rapid prototyping, this ability to evaluate multiple design options in a fraction of the time it would take manually is revolutionary [60]. In predictive maintenance, where AI models assess the condition of the equipment in real time and anticipate potential failures before they occur, GAI is critical [61]. This improves safety, lowers maintenance costs, and decreases downtime, especially in vital sectors, such as manufacturing, energy, and transportation.

Additionally, supply chain management and other engineering processes can be improved using GAI, thereby reducing costs and inefficiencies [62]. AI models can estimate demand, identify bottlenecks, and optimize logistics by evaluating data from multiple supply chain locations, leading to more efficient and economical operations [63]. Furthermore, by assisting engineers in creating infrastructure and systems that are more resource efficient, emit fewer emissions, and consume less energy, GAI has the potential to promote sustainable engineering practices.

2.4. Mitigating Challenges Through Targeted Strategies

A variety of targeted strategies derived from research can help mitigate the risks associated with adopting GAI to address the issues mentioned above. Strong governance and ethical frameworks must be developed to guarantee responsible use [64]. Educational institutions must create comprehensive rules and procedures that include topics such as accountability, algorithmic bias, and data protection. These organizations must also ensure that they follow changing laws related to the use of data and the use of artificial intelligence [65]. Creating fair frameworks that protect people and institutions while fostering innovation will require a collaborative study with experts in ethics, law, and AI governance. Moreover, overcoming the resistance to adopting GAI requires creating institutional support and providing opportunities for professional growth [66]. This is accomplished by providing training sessions and seminars that highlight the potential of GAI, which can build confidence in its application and highlight its value as a tool for improving engineering and academic processes [67]. As these activities promote a culture of cooperation and shared learning, peer learning and sharing of best practices should also be promoted [68]. In this manner, stakeholders may improve their overall institutional preparedness by working together to develop the knowledge required to successfully incorporate GAI into their processes.

Finally, to guarantee that the tools satisfy the needs of the people who will be using them, a user-centered approach to GAI design and cooperation is essential [69]. For GAI systems to be user-friendly, efficient, and in line with institutional objectives, academics,

researchers, and engineers must be involved in their design. Furthermore, feedback loops must be established to continually assess the efficacy of GAI systems and make the required modifications to enhance the results and usability over time.

In conclusion, there are many challenging obstacles and exciting potential when integrating GAI into engineering and academic fields [70]. These industries may fully utilize GAI technology by addressing ethical issues, overcoming institutional opposition, and developing customized integration techniques. Table 1 provides a detailed summary of the significant factors identified in this literature review. These challenges are pivotal considerations for the next phase of our research, in which we systematically evaluate their influence. This evaluation will determine the factors that play a crucial role in enabling the effective integration of GAI technologies in academic and engineering disciplines, paving the way for a robust framework for their successful adoption.

Table 1. Factors Influencing GAI Implementation in academic and engineering disciplines.

Categories	Factors	Ref.
Educational Enhancement	**Quality of GAI Output**: Ensuring accurate and meaningful outputs for learning and understanding.	[19,24,44]
	Assessment Automation and Integrity: Enabling fair and efficient grading through automation.	[39,42]
	Explainability: Simplifying GAI results for easier understanding and use.	[39,46,69]
	Personalization and Adaptivity: Adapting content to individual learning needs and styles.	[40,52,54]
	Content Accuracy and Relevance: Keeping GAI-generated content up-to-date and precise.	[42,58]
	Critical Thinking Stimulation: Encouraging students to analyze and think deeply.	[57,64]
	Continuous Learning Support: Facilitating ongoing learning and skill development.	[57]
	Ethical and Responsible Research Practices: Promoting ethics and integrity in research.	[64,67,68]
	Interactive Feedback: Providing quick and actionable feedback to enhance learning.	[37],
	Content Personalization: Customizing educational content based on student progress and needs.	[39,40]
	Accessibility and Inclusivity: Ensuring equitable access for all students, including those with disabilities.	[44]
	Adaptability to Learning Styles: Catering to diverse learning preferences.	[18]
	Ethics and Privacy Concerns: Protecting sensitive data and promoting ethical AI use.	[33]
	Skill Enhancement: Providing training to build expertise in using GAI effectively.	[37,67]
Research Advancements	**Idea Generation and Conceptual Development**: Inspiring creative ideas and innovative research.	[50,59]
	Data Analysis and Insight Generation: Analyzing large datasets to generate valuable insights.	[43,56]
	Analysis and Synthesis: Summarizing and understanding complex research data.	[30,46]
	Research Dissemination: Enhancing access to and understanding of research outputs.	[30]
	Knowledge Transfer: Sharing insights and best practices across disciplines.	[18,52]
	Data Collection: High-quality data acquisition; Relevance assessment for GAI model training.	[42,56]
	Algorithm Optimization: Improving the efficiency and accuracy of AI algorithms.	[22,25,59]
	Conceptual Clarity: Making complex ideas and concepts easier to understand.	[43,52]
Administrative Efficiency	**Administrative Efficiency**: Automating routine tasks to save time and resources.	[44,45,60]
	Resource Allocation: Ensuring adequate funding and availability of GAI tools.	[63]
	Scalability: Ensuring GAI systems can expand with increasing demands.	[29]
	Feedback Mechanisms: Using user feedback for ongoing system improvement.	[29]
Ethical and Governance	**Bias Mitigation**: Addressing and reducing biases in AI outcomes.	[25]
	Compliance Standards: Ensuring adherence to regulations and ethical guidelines.	[34]
	Model Transparency: Promoting understanding of how GAI systems function.	[30]
	Privacy Protection: Safeguarding sensitive information during GAI use.	[33]
Collaborative Innovation	**Interdisciplinary Collaboration**: Fostering collaboration across diverse fields.	[67]
	Collaborative Platforms: Providing tools to support teamwork among students and faculty.	[67]
	Collaborative Problem-Solving: Encouraging group efforts to tackle complex problems.	[62,67]

Table 1. *Cont.*

Categories	Factors	Ref.
	Professional Development and Networking: Supporting faculty in finding growth opportunities.	[41]
Student Engagement	**Real-world Application**: Demonstrating the practical relevance of learning through GAI.	[42,44,59]
	User Experience: Enhancing the usability and satisfaction of GAI tools.	[59,64]
Technological Integration	**Integration with Educational Tools**: Ensuring GAI integrates seamlessly with existing platforms.	[36,44,57]
	Algorithm Selection: Choosing the best GAI models for specific tasks.	[25,32]
	Contextual Understanding: Using GAI to interpret and apply contextual insights.	[39]
	Community Engagement and Outreach: Using GAI to understand and meet community needs through targeted programs	[40]
	Resource Identification: Helping students find the tools and materials they need.	[57]
	Model Updating: Continuous learning mechanisms; adaptation to new data and feedback.	[33,63]
	Data Accessibility: Make sure students can easily obtain the data they need.	[44]

This study demonstrates a revolutionary opportunity to improve efficiency, creativity, and productivity through the use of generative AI in engineering and academia. However, there are a number of hurdles to its acceptance, such as institutional opposition, legal barriers, ethical issues, and lack of user experience. A comprehensive strategy that tackles these hurdles via strong ethical foundations, educational initiatives, and multidisciplinary cooperation is necessary for successful integration. GAI has the potential to transform engineering and educational methods by emphasizing elements like sustainability, operational optimization, and individualized learning. GAI has the ability to significantly progress both industries, encouraging innovation and enhancing results overall, given the proper governance and tactics.

3. Materials and Methods

This section outlines the methodological approach employed to investigate the integration of GAI technologies and their impact on productivity in the context of engineering education. Recognizing the complex and multifaceted nature of GAI adoption, this study employs a mixed-method design comprising two sequential stages: an initial qualitative phase focused on validating key factors, followed by a quantitative phase aimed at prioritizing these factors and assessing their relative importance.

The selection of methods reflects this study's objective to bridge the gap between theoretical understanding and practical realities. By engaging engineering students and faculty as key stakeholders, this research ensures that the findings are grounded in both academic perspectives and real-world experiences. This two-stage approach enables a comprehensive analysis of the challenges, opportunities, and critical conditions for effective GAI adoption, ultimately providing a robust evidence base for actionable recommendations.

3.1. Stage 1, Factors Validation

The first stage of this study, Factors Validation, is important in aligning theoretical frameworks with real-world applications, ensuring the effectiveness of subsequent research stages and establishing them in practical relevance. At this stage, the focus is solely on semi-structured interviews to answer the first research question: identifying hurdles to the application of GAI technologies in the selected research areas. These interviews were designed to explore issues associated with the integration of Generative AI and confirm significant factors described or gathered in the literature review section. This stage, conducted on a small, carefully selected sample of two types of participants, focuses on the legitimacy and depth of the ideas collected. Participants from the American University of Sharjah (AUS) comprise academic faculty members such as deans, professors, and

engineering students from six engineering departments, as seen in Table 2, which is noted for its technological accomplishments and diversified academic environment.

Table 2. Stakeholders in this study.

Field	Participant	Major
Academia and Engineering	Engineering Students (Bachelor's, Master's, Doctorate and Postgraduate Programs) Faculty Members (Dean, Professor, and Associate Professor)	• Chemical and Biological Engineering (ChE/CBE) • Civil Engineering (CE) • Computer Science and Engineering (CSE) • Electrical Engineering (EE) • Industrial Engineering (IE) • Mechanical Engineering (ME)

With their knowledge and expertise in GAI technology, these experienced experts and students offer unique perspectives that represent academic achievement and practical experience. Also, participants' rights and privacy are strictly protected throughout the study procedure. Before the interviews begin, participants must complete informed consent papers. These forms explicitly state the purpose of this study, the voluntary nature of participation, and the safeguards in place to maintain the confidentiality of participants' identities. The research strategy used at this stage was appropriate to the exploratory nature of the investigation, and the qualitative methods used in this study strongly sought to gain participants' views, leading to a comprehensive understanding of the issue.

Moreover, interview questions, carefully crafted based on topics from the literature study, centre on participants' knowledge with GAI technologies, their perceived association with productivity, and implementation factors. This technique ensures a comprehensive analysis of the difficulties and helps to refine the identified factors. To evaluate the results of the interviews, appropriate data collection software, such as Excel, was used to analyze the data based on faculty and student responses. This approach helped identify barriers to GAI implementation, ultimately leading to enhanced productivity at the study sites.

Hence, Stage 1 produces a thoroughly confirmed list of factors that will serve as the foundation for this research's succeeding stages. These results will directly guide the formulation of survey questions in Stage 2, when this study is expanded to include a larger sample size to analyze the relative importance and impact of these factors on productivity.

3.2. Stage 2, Prioritization of Factors: Expert Evaluation and Insights

The second stage of this study, Prioritizing Factors: Expert Assessment and Insights, focuses on analyzing the factors discovered and validated in Phase 1 on a larger scale. This phase seeks to assess the relative importance and impact of these factors in integrating GAI technologies into academic and engineering settings. The results of this phase provide key insights for setting standards and developing strategies for implementing effective GAI.

Based on the results of the first phase, this phase uses a survey-based strategy to collect data from a larger number of participants. The survey questions were carefully designed based on the results of the interviews in the first phase. These questions are designed to measure the perceived importance of each previously identified factor and collect quantitative data about its value. Participants at this step involve a larger range of stakeholders, including faculty members, engineering students, and other relevant specialists from the selected university. This larger number of participants ensures that the results reflect a variety of opinions and experiences within the research environment. The survey approach used in this step involves providing structured questionnaires to participants. This survey uses a Likert scale to rate the importance of each factor, allowing respondents to rate them based on their importance and impact on productivity. The data collected from these surveys is then examined using the Relative Importance Index (RII), a

powerful analytical technique often used in factor ranking investigations [71]. This index provides a quantitative picture that helps in ranking factors according to their priority or relative importance by using the equation below:

$$\mathrm{RII} = \frac{\sum \mathrm{w}}{\mathrm{AN}} = \frac{5\mathrm{n}_5 + 4\mathrm{n}_4 + 3\mathrm{n}_3 + 2\mathrm{n}_2 + 1\mathrm{n}_1}{5 \times \mathrm{N}} \quad (1)$$

The process of calculating the RII begins by assigning a weight (w) to each factor based on the respondents' ratings, where this weight ranges from 1 (low importance) to 5 (high importance). Next, the product of each weight and the number of respondents who assigned that weight to the factor (n) is calculated, and these products are added together to obtain a weighted total. This total is divided by the product of the highest weight (A) which is 5, and the total number of respondents (N) to obtain the RII value. Since survey participants were divided into two groups: faculty member and students, which means the RII will be used twice. The survey results are separated and examined for faculty and students to uncover possible discrepancies in their judgments of factor relevance. The data stratification process ensures that this research reflects differences in experience and priorities between groups, making this study more relevant to the needs of each stakeholder. Therefore, the second phase ranks the factors by importance, addresses the second research question, and identifies the key factors driving the adoption of GAI in academic and engineering disciplines. The findings provide practical insights into stakeholder-specific tactics based on both qualitative and quantitative evidence.

This stage combines exploratory insights from Stage 1 with practical recommendations to deepen our understanding of productivity-related factors within the academic and engineering education context. As an exploratory investigation, this study seeks to capture participants' context-specific experiences and interpretations of how GAI tools are being introduced, adapted, and evaluated within their institutions. The perspectives gathered are therefore grounded in real teaching, research, and administrative practices, reflecting how faculty and students operationalize GAI in their academic routines. While some of the concerns raised, such as ethics, bias, and training, mirror broader global discussions on GAI, in this study they are expressed through the unique lens of engineering disciplines, where issues like model transparency, data validation, and accuracy are particularly critical.

Accordingly, Figure 1 outlines the data collection and analysis procedures, emphasizing that the results represent context-bound insights specific to engineering education and are not intended to be generalized to society or other sectors. The exploratory design therefore captures how global themes surrounding GAI are experienced and negotiated at the local institutional level, contributing original, practice-based evidence to the ongoing academic discourse on AI in education.

This study's two-stage methodology therefore integrates qualitative interviews and quantitative surveys to capture early, experience-based perspectives on GAI adoption within engineering education. This mixed-method approach validates and prioritizes factors identified in Stage 1 while preserving their exploratory depth. By linking participants' lived experiences with statistical prioritization, the design ensures that the findings remain grounded in real institutional and disciplinary practices, offering nuanced evidence of how global discussions on GAI are interpreted and applied in engineering-specific educational contexts.

The next section presents the results, highlighting key factors and their relative importance in fostering effective GAI integration in engineering education.

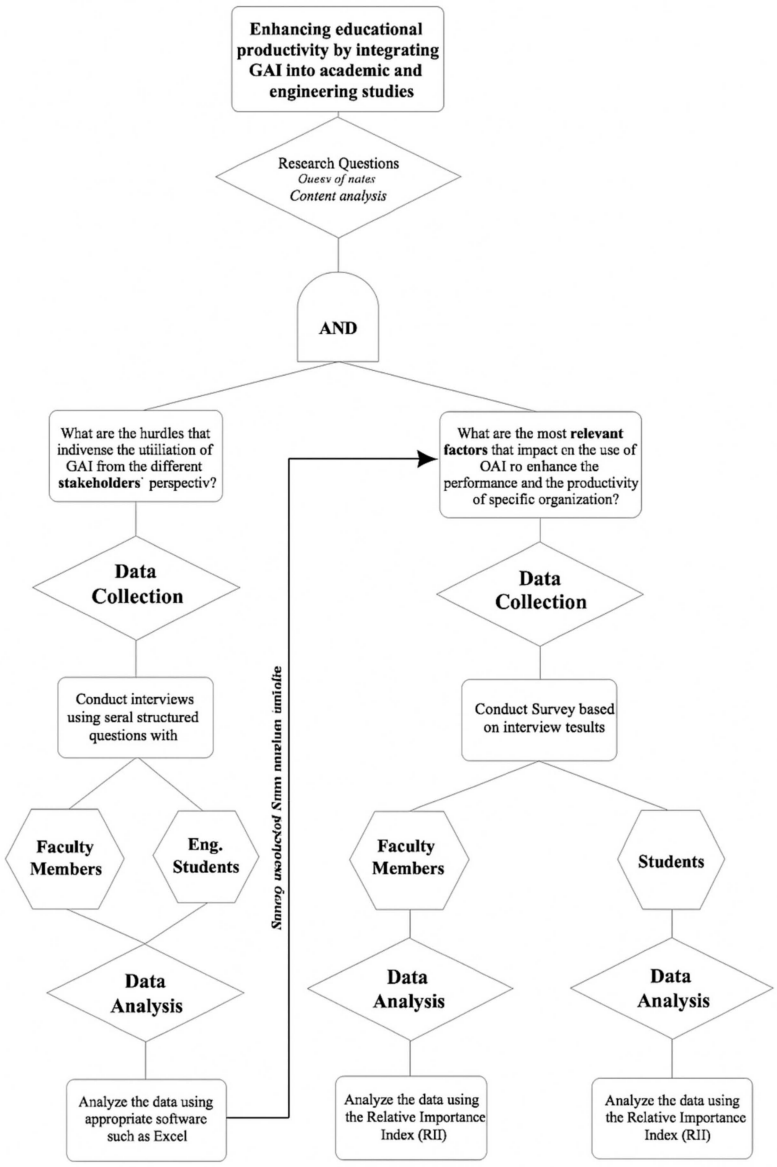


Figure 1. Data tree diagram for collection and analysis to all processes.

To ensure analytical clarity, the qualitative findings presented in Section 4 are drawn exclusively from primary interview data collected from faculty and students. References to previous studies are included only to support or illustrate participants' perspectives, helping to contextualize the empirical observations without merging them with theoretical insights. This approach preserves the authenticity of the field evidence while ensuring that the analysis remains grounded, transparent, and aligned with established academic practices.

4. Results

This section provides an overview of the collection and evaluation of data from two stakeholder groups: faculty and students at the chosen case study university. Also, the interviews will be treated first as a sub-section, followed by data obtained from a survey of a large number of participants in both groups, and this procedure will be carried out sequentially.

4.1. Factor Validation and Consolidation: Semi-Structured Interviews

4.1.1. Students' Interview

The factors derived from literature research on the use of GAI in engineering and academia were refined through in-person and online interviews. Table 3 shows the participation of the 14 undergraduate and graduate students from six engineering departments: industrial, chemical, mechanical, civil, computer, and electrical. Each 30 min interview focused on key aspects of integrating general AI and students' familiarity with the technology.

Table 3. Profile of students Interviewed.

Department	Total Years/Current	State/(Current)	Code
Electrical Engineering	4th year	Undergraduate Student	ELE [S1]
Electrical Engineering	4th year	Undergraduate Student	ELE [S2]
Chemical and Biological Engineering	4th year	Undergraduate Student	CHE [S1]
Chemical and Biological Engineering	1st year	Graduate student (Master)	CHE [S2]
Mechanical Engineering	4th year	Undergraduate Student	MCE [S1]
Mechanical Engineering	4 years	Undergraduate Student	MCE [S2]
Computer Science and Engineering	5 years	Graduate student	CMP [S1]
Computer Science and Engineering	4 years	Graduate student	CMP [S2]
Civil Engineering	2nd year	Graduate student (Master)	CVL [S1]
Civil Engineering	3 years	Graduate student	CVL [S2]
Industrial Engineering	3rd year	Graduate student (PhD)	IND [S1]
Industrial Engineering	2nd year	Graduate student (Master)	IND [S2]
Industrial Engineering	2nd year	Graduate student (Master)	IND [S3]
Industrial Engineering	1st year	Graduate student (Master)	IND [S4]

Familiarity with GAI and Technology Awareness from the Students' Perspective

Interviews indicated a significant disparity in knowledge related to GAI across engineering disciplines. For example, computer engineering students demonstrated advanced skills in programming and debugging GAI, while industrial and mechanical engineering students had only a rudimentary understanding. Some outliers were found, including a chemical engineering student working on a thesis focused on GAI, and an industrial engineering student familiar with applications of GAI in healthcare and robotics.

These findings, as shown in Figure 2a, highlight the need for specialized training and targeted approaches to integrating GAI, underscoring the need for resources to bridge knowledge gaps. Based on academic focus or personal interest, CMP [S2] and CHE [S2] used GAI extensively, while IND [S3] showed minimal familiarity. Interdisciplinary fields, such as IND [S1], report a better understanding, likely due to exposure to a wider range of applications. The absence of "Not familiar" responses suggests that engineering students generally possess basic GAI knowledge, supporting the case for further integration of GAI into educational contexts.

To further contextualize this familiarity, Figure 2b shows the course categories that students believe would benefit most from GAI integration. Given its ability to handle complex problems and support writing, students determined that GAI courses were most suitable for computer science, science, English, and mathematics. Overall, it was widely agreed that GAI can enhance both writing and programming skills across various disciplines. This pie chart highlights a strong link between productivity and the integration of GAI technologies, which are seen as enhancing competence, learning, and skill development, particularly in precision-critical areas.

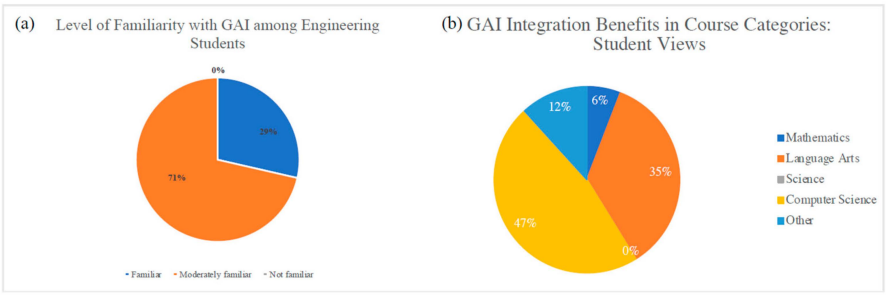


Figure 2. (**a**,**b**) Combined Insights on GAI in Engineering Education: (**a**) Pie chart of GAI familiarity level among engineering students; (**b**) Distribution of Course Categories Benefiting from GAI Integration through Student Perspectives.

Additionally, participants offered diverse yet positive definitions of GAI, emphasizing its role in enhancing productivity, creativity, and academic quality. ELE [S1] and ELE [S2] emphasized its research and writing benefits, while Computer Engineering students focused on automation and business potential. CHE [S1], CHE [S2], and MCE [S1] provided technical perspectives, seeing GAI as a tool for synthesis, problem-solving, and innovation. Though CVL [S2] and IND [S1] have limited experience, they acknowledge its growing relevance. A word cloud analysis (Figure 3) confirms the recognition of GAI's academic and professional benefits.



Figure 3. Word Cloud Representation of Students' Definitions and Perceptions of GAI.

According to students' responses, the frequent use of terms like "**GAI**" and "**Artificial Intelligence**" in the word cloud demonstrates students' great awareness and grasp of these technologies. Terms such as "**Generative**" and "**Content**," highlight students' appreciation for GAI's ability to produce unique and innovative academic resources, while "**Academic**" indicates a significant impact on their education. Lastly, students view GAI as a tool to enhance "**Efficiency"**, "**Creativity"**, and "**Productivity"** in their academic pursuits.

As shown in Figure 4, participants demonstrated varying levels of familiarity with GAI tools, with ChatGPT (GPT- 4) being the most widely used due to its accessibility in educational settings. They discussed anticipated challenges and provided recommendations for effective use in learning and research.

According to the interviews, students are familiar with some GAI tools, such as BERT and Google Bard, which are often used for text analysis, but others, such as Ada, Jasper AI, ChatSpot, and Cloud, are less well-known and require more experience. Common concerns about GAI in education include repetitive responses, context retention, data protection, and integration barriers. To address these issues, students suggested improvements such as introducing validation procedures, customizing tools, improving integration, and providing ongoing training to increase effectiveness and stimulate critical thinking.

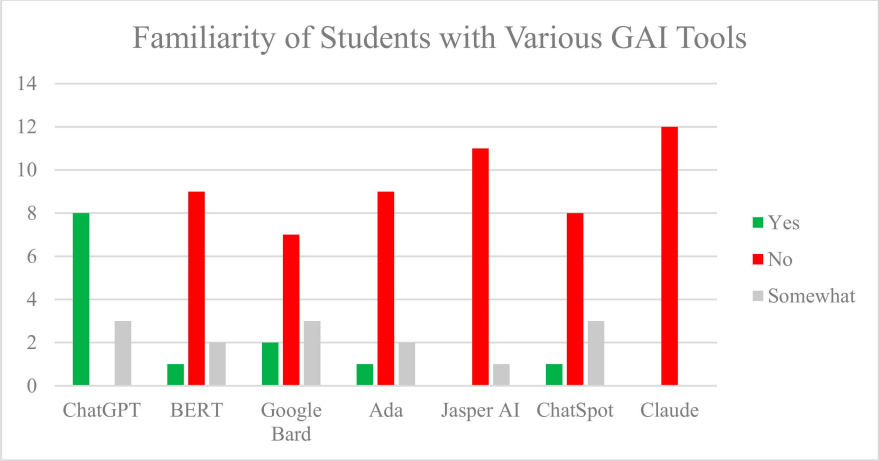


Figure 4. Students Familiarity with Generative AI Tools.

To strengthen analytical transparency, the field data were examined using a dual-phase mixed-method approach. In the first phase, quantitative data from questionnaires were statistically analyzed to identify the most frequently used GAI tools and their perceived effects on productivity and learning performance. In parallel, qualitative data from semi-structured interviews were subjected to thematic analysis, yielding recurrent patterns of challenges and recommended practices. These two datasets were then cross-referenced through a correlation mapping matrix that aligned the frequency and thematic relevance of each challenge with the tools most often cited in connection with it. The resulting matrix served as the analytical foundation for Figure 5, which visualizes these empirically derived relationships. Specifically, the red lines represent challenges commonly associated with multiple tools, while the blue lines depict the actions most frequently proposed by participants to address those issues. This integrative visualization thus translates the coded interview themes and survey statistics into a coherent, data-driven map of student perspectives on GAI challenges and mitigation strategies in education.

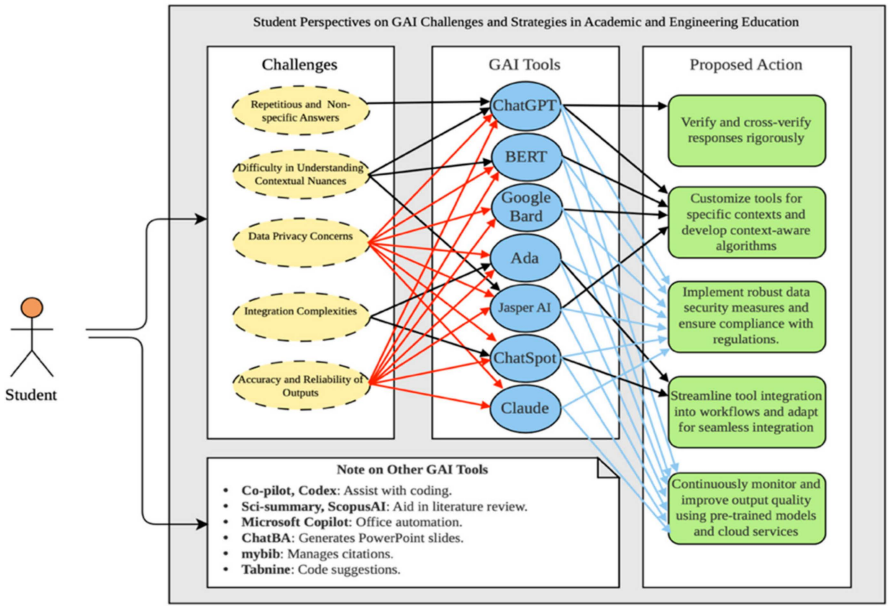


Figure 5. Visualization of Challenges and Actions for GAI Tools in Education: Student Opinions.

Factors Influencing the Adoption of GAI Technology in Enhancing Productivity: Students' Perspective

There are a number of issues, including governance and compliance, with a particular focus on ethics, privacy, and data security, that will determine whether GAI is used in educational institutions, particularly in the engineering and academic sectors. While preventing bias is viewed as less critical, data accessibility and quality are seen as essential for effective use, particularly with task-specific algorithms. GAI greatly enhances learning by facilitating the understanding of complex material, improving content comprehension, and highlighting the value of producing high-quality work.

Although there were mixed opinions about the openness of the model and the improvement of the algorithms, most participants agreed that regular updates and feedback channels are essential for continuous development. Furthermore, scalability and user capabilities were recognized as crucial to handling growing workloads. For GAI to be effective in education, it must be able to adapt to different learning styles, encourage critical thinking, and facilitate group problem-solving. GAI improves research and project work by supporting data analysis, idea generation, and resource management. Also, it was believed that the successful implementation of GAI would require accessibility, ethical considerations, and seamless integration with existing systems.

4.1.2. Faculty' Interview

This subsection outlines the interview procedures with academic members from the College of Engineering, including professors, lab instructors, and deans. A total of 13 academics participated in face-to-face and online interviews, lasting 25 to 40 min each. The interview questions, derived from the literature review, aimed to achieve three objectives: (1) assess participants' familiarity with and awareness of GAI technology, and (2) identify key factors for integrating GAI into environmental institutions. Table 4 shows the profiles of the interviewees.

Table 4. Profile of Faculty Interviewed.

Department	Position	Total Experience	Code
Chemical and Biological Eng.	Professor and Head	27 years	CHE [F1]
Chemical and Biological Eng.	Associate Professor	11 years	CHE [F2]
Electrical Engineering	Associated Professor	12 years	ELE [F1]
Electrical Engineering	Post-Doctoral Fellow	15 years	ELE [F2]
Computer Science and Engineering	Professor	30 years	CMP [F1]
Computer Science and Engineering	Professor	35 years	CMP [F2]
Industrial Engineering	Professor	24 years	IND [F1]
Industrial Engineering	Professor and Head	14 years	IND [F2]
Civil Engineering	Professor	21 years	CVL [F1]
Civil Engineering	Professor	30 years	CVL [F2]
Civil Engineering	Professor	18 years	CVL [F3]
Mechanical Engineering	Visiting Professor	7 years	MCE [F1]
Mechanical Engineering	Professor and Head	21 years	MCE [F2]

Familiarity with GAI and Technology Awareness from the Faculty's' Perspective

Students and faculty members varied in their level of familiarity with GAI, with most indicating that they were "familiar" or "Moderately familiar", as shown in Figure 6. ELE [F1] demonstrated how well GAI can be integrated into academic procedures, confirming

its usefulness in assisting both teaching and learning. Others (CHE [F1], MCE [F1], CMP [F2], CVL [F2], and IND [F2]) showed a gap between familiarity and active use, with widespread knowledge but limited engagement.

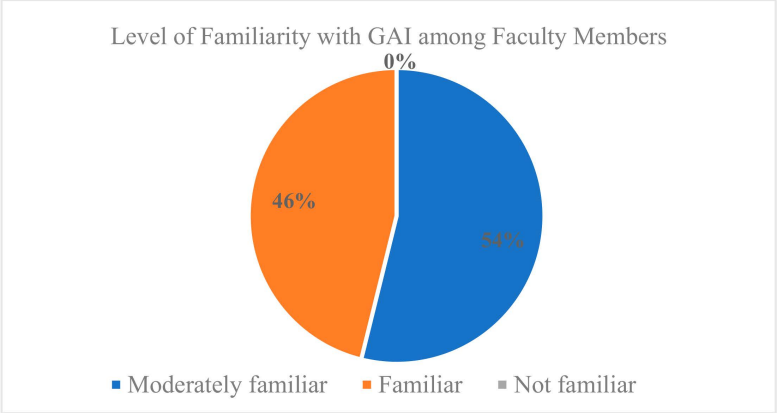


Figure 6. Pie chart of GAI familiarity level among the faculty members.

However, a few participants (ELE [F2], CMP [F1], and IND [F1]) provided specific examples of how they used GAI to improve information retrieval, create instructional materials, and improve classroom projects. According to faculty feedback, those who were more familiar with the GAI tended to integrate it better overall, strengthening the connection between application and knowledge in academic contexts.

When defining GAI, participants viewed GAI as a multifaceted tool with important academic ramifications; supporters pointed to how it improves research, teaching, and learning through personalization and interactivity, while critics expressed concerns about its potential impact on creativity and critical thinking. Its practical uses, such as accelerating research, transforming teaching, and automating functions like writing and editing, point to its potential, but the lack of awareness among some participants highlights the need for more education about its broader implications.

As seen in Figure 7, these results were supported by a word cloud analysis, which revealed "**GAI**" to be the most commonly used term, highlighting its crucial significance in academic innovation.



Figure 7. Word Cloud Representation of Faculty Definitions and Perceptions of GAI.

While "**Academic**" and "**Research**" emphasized its significance to faculty work and idea production, words like "**Time**" demonstrated its effectiveness in research and teaching. "**Engineering**" also highlighted its function in data analysis and problem-solving. Although

GAI has many potential advantages, its successful integration into academia necessitates individualized assistance for instructors while addressing issues with critical thinking and creativity.

As shown in Figure 8, this study found variance in faculty members' familiarity with GAI tools, with ChatGPT being the most popular and preferred tool for gathering information and generating text. However, further training is still needed, as some faculty members, are unfamiliar with technologies such as Ada, Jasper AI, and ChatSpot. Faculty members in the mechanical and electrical engineering departments demonstrated greater knowledge, indicating a more proactive approach to the use of GAI.

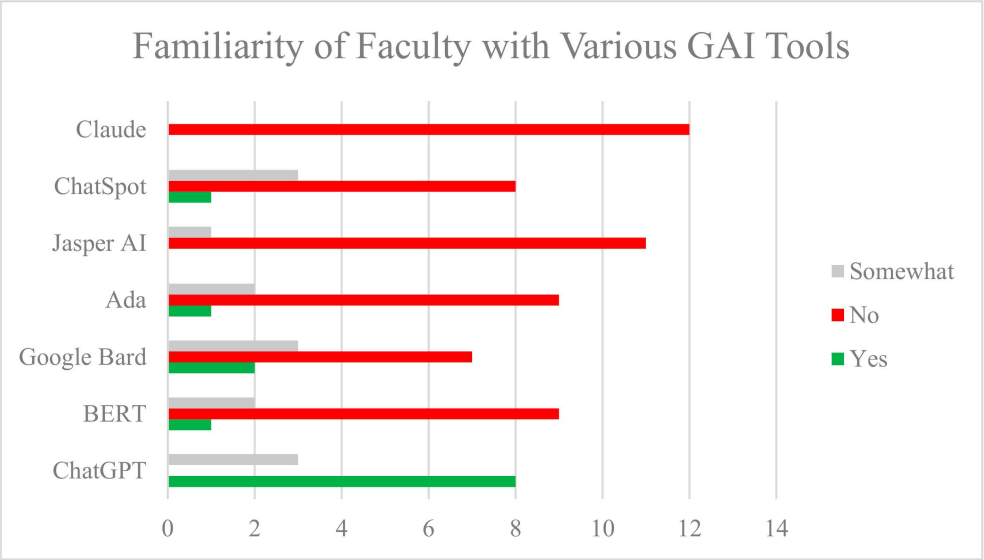


Figure 8. Faculty familiarity with Generative AI tools.

The data shows that faculty members in the electrical and mechanical engineering fields have expressed concerns about the authenticity and confidentiality of the data, raising doubts about the validity, accuracy, and reliability of the information generated by GAI. To illustrate more, issues such as the need for resources to maintain GAI models, and restricted access to some tools, such as Ada and Google Bard, were also mentioned. Therefore, faculty members suggested addressing these issues by carefully selecting tools, validating information derived from GAI, and providing comprehensive training and support mechanisms for integrating GAI into scientific research.

As with the Student Interviews section, below is an overview of challenges, recommended actions, and other additional tools for faculty insight. In Figure 9, academics have seen the potential of GAI tools, such as Grammarly for writing and Microsoft Copilot for scientific visualizations, as well as experimental programs like Does Sora and Gemini for multimedia creation. To ensure the optimal use of GAI in academia, faculty members emphasized the need for ongoing training, validation, and adherence to ethical standards.

In conclusion, the planned strategies, shown in cyan, aim to successfully solve these problems. In this scenario, the most major obstacle is training, guidelines, and continuous learning, and the most successful proposed remedy is to establish guidelines, hold seminars, and provide ongoing training assistance.

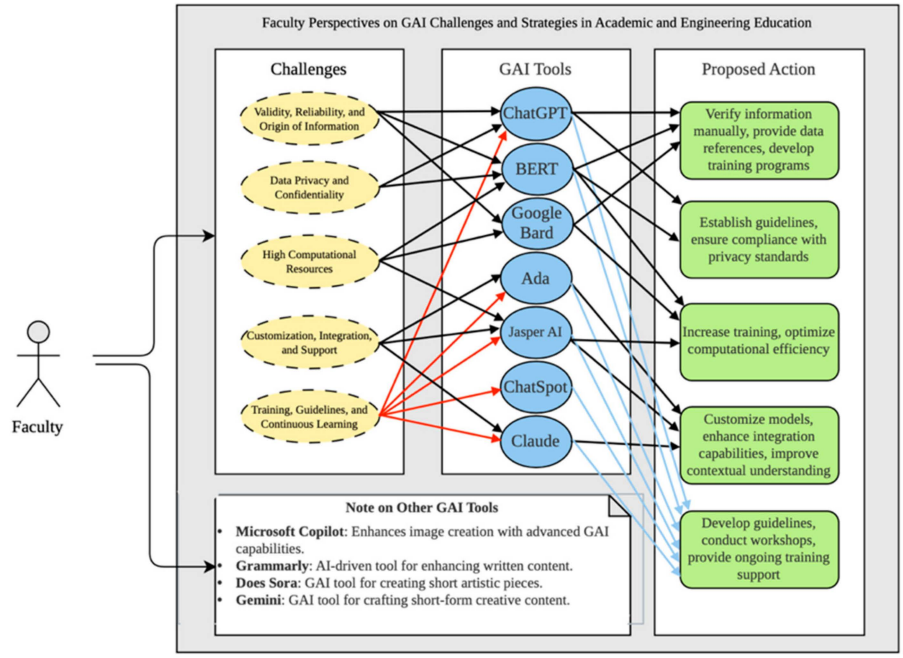


Figure 9. Visualization of Challenges and Actions for GAI Tools in Education: Faculty Opinions.

Factors Influencing the Adoption of GAI Technology in Enhancing Productivity: The Faculty Members' Perspective

Focusing on teaching, research, and service, this study examined the factors influencing faculty acceptance of GAI in academic and engineering settings. Performance, improvement, governance, and compliance surfaced as major themes. Although there were differing perspectives on compliance needs and prejudice avoidance, ethics and privacy were crucial.

To promote effective learning and research, faculty participants emphasized the importance of explainability and output quality when using GAI tools, noting that transparent algorithms and interpretable outputs are essential for maintaining trust in academic work. Many respondents linked these concerns to the need for robust data and resource management, stressing that accessibility to reliable datasets and equitable resource distribution are prerequisites for meaningful GAI integration, particularly in engineering disciplines where accuracy and validation are paramount. Participants also highlighted that continuous improvement of GAI applications requires active feedback mechanisms, enabling users to refine models and teaching materials over time.

The findings further revealed that training and digital skill development represent a persistent institutional gap rather than a general observation. Faculty members reported that existing training opportunities are often limited in scope and not tailored to engineering contexts, resulting in uneven levels of adoption across departments. While this finding aligns with prior research emphasizing the importance of digital competency, it emerged directly from participants' lived experiences of managing GAI in their teaching and research activities.

Regarding collaborative platforms, opinions diverged: some faculty valued them as tools for fostering interdisciplinary teamwork and knowledge exchange, whereas others perceived them as underutilized due to insufficient institutional support and lack of targeted training. These contrasting views highlight that participants were not merely repeating established ideas from the literature but were interpreting well-known challenges through the lens of their daily academic realities. These insights confirm that effective GAI adoption in academia depends on aligning institutional resources, training programs, and

collaboration initiatives with the actual needs and constraints experienced by faculty in their professional practice.

Though questions regarding need and fairness still exist, GAI is appreciated in education for automating grading and customizing instruction. In research, it is critical for data analysis and technique creation, with significant support for ethical principles. GAI improves administrative efficiency but has varying effects on community participation. It is popular in technical courses such as electrical and computer engineering, although care is advised in civil and mechanical engineering. Overall, GAI's academic integration should be deliberate, ethical, and field-appropriate.

Faculty members from several engineering disciplines highlighted essential courses that would benefit from GAI integration, emphasizing its importance in increasing productivity and simplifying complicated procedures. Electrical engineering stressed coding and antenna design, whereas mechanical engineering focused on programming, FEM, CFD, and CAD, emphasizing the need of computational support. Similarly, chemical engineering advised electives such as water treatment and energy transition, while computer science recommended basic disciplines such as mathematics, physics, and decision-making courses, which even included humanities. Furthermore, industrial engineering suggested research methodology, performance management, and engineering management, emphasizing GAI's function in research and management. In contrast, civil engineering professors exhibited little excitement for GAI use, indicating a cautious attitude. Figure 10 depicts these varying viewpoints across engineering fields as a summary map.

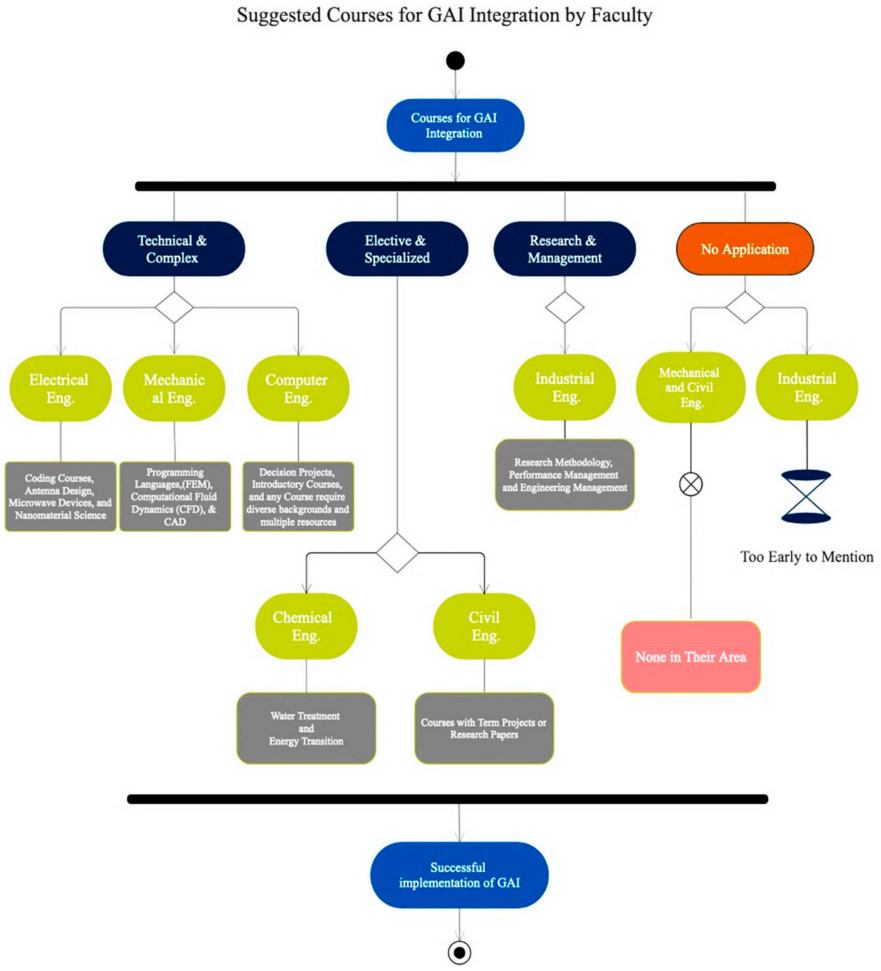


Figure 10. Summary of courses proposed for GAI integration by faculty.

4.1.3. Summary of Stage 1

The overview focused on faculty and student recommendations for effectively integrating GAI into academic and engineering environments.

Students emphasized practical experience, interdisciplinary initiatives, standardized programs to address knowledge gaps, continuous updates on GAI, ethical standards, and user-friendly interfaces. While faculty suggested regular training, seminars, originality in research, and clear ethical guidelines to foster critical thinking. They also highlighted interdisciplinary collaboration and change management techniques to enhance teaching and productivity. Table 5 summarizes their recommendations for successful GAI integration.

Table 5. Summarization of Faculty and Student ideas and recommendations about successful GAI integration.

Category	Students	Faculty
Positive Reflections	• Increase efficiency and productivity in jobs such as programming and daily academic work. • Enhanced creativity and innovation through GAI tools. • Better organization and presentation of academic work.	• Seen as beneficial for enhancing teaching and productivity. • Use GAI to prepare for lectures, class projects, and community conversations. • High knowledge leads to broad engagement with GAI. • Interest in the utility of the GAI is growing in academia. • Global recognition of importance. • Enhances productivity by streamlining tasks. • Interdisciplinary collaborations enhance exploration of GAI applications.
Negative Reflections	• Knowledge gaps and a weak comprehension of GAI. • Inconsistent implementation of GAI across programs. • GAI results suffer from issues of specificity and reproducibility.	• Concerns about diminishing critical thinking and innovation. • Some Faculty lack deep integration of GAI into their work. • Some faculty show varying levels of engagement. • Concerns about ethical use and data privacy. • Resistance to change due to altering current practices.
Proposed Recommendations	• Increase practical projects and industry collaborations. • Encourage multidisciplinary projects and workshops. • Implement comprehensive educational programs for GAI. • Develop standardized GAI curricula across disciplines. • Offer certification programs and advanced courses. • Emphasize ethical use and development of best practices. • Improve GAI tool usability and provide effective training.	• Provide ongoing training to familiarize faculty with advanced GAI tools and applications. • Encourage innovative integration of GAI into course materials and projects. • Implement structured training for varying levels of familiarity. • Conduct seminars to address concerns and highlight GAI's cognitive benefits. • Develop ethical guidelines and protocols for GAI use. • Develop change management strategies showcasing successful case studies.

To analyze the qualitative findings systematically, this study adopted a contextualized SWOT framework tailored to the exploration of GAI adoption in higher education. While traditional SWOT distinguishes internal elements (strengths and weaknesses) from external ones (opportunities and threats) at the organizational level, in this study the framework

was adapted to reflect the educational ecosystem. Internal factors refer to institutional and individual capacities, including teaching practices, digital literacy, infrastructure, and organizational readiness to integrate GAI. External factors encompass contextual and environmental influences, such as government regulations, evolving AI policies, ethical standards, industry expectations, and global technological trends.

This adapted SWOT approach was used to synthesize participant insights into a structured format that captures the interplay between institutional conditions and external pressures affecting GAI implementation. Figures 11 and 12 illustrate this analysis separately for students and faculty to highlight differences in perspective and detail. Despite the difference in visual layout, both figures follow the same conceptual framework, emphasizing how internal capabilities interact with external drivers and constraints in shaping the effective integration of GAI in engineering and academic contexts.

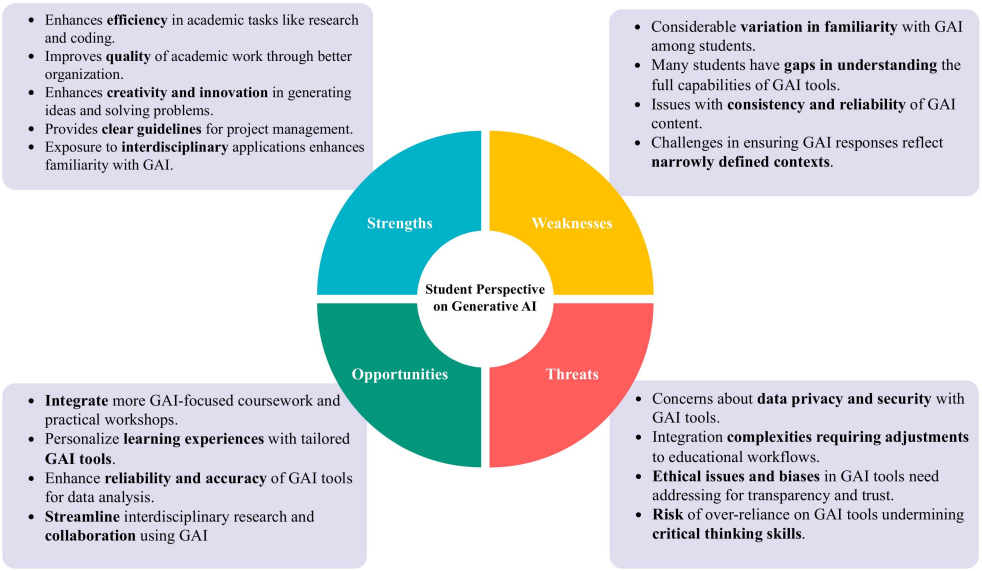


Figure 11. SWOT analysis of GAI implementation in engineering and academia from Students' perspective.

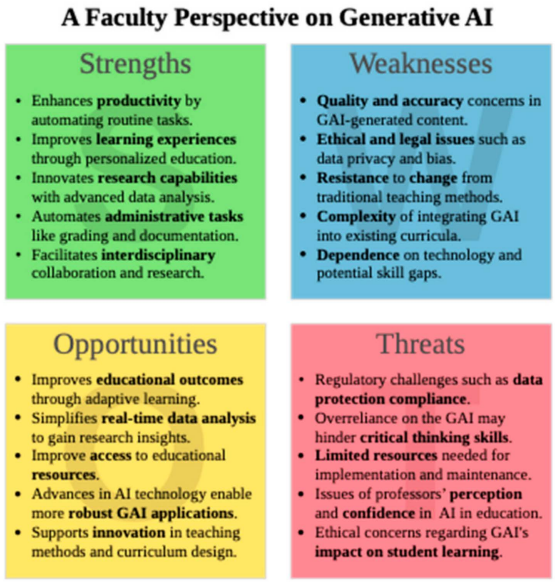


Figure 12. SWOT analysis of GAI implementation in engineering and academia from Faculty perspective.

Based on the above two SWOT analyses, the identified hurdles for students and faculty are summarized in detail in the following points:

Students' hurdles:

- Familiarity and Education—Limited awareness and lack of structured learning resources.
- Practical Application—Need for real-world applications in GAI training.
- Context and Reliability—Ensuring accurate and consistent responses from GAI.
- Ethical and Privacy Concerns—Addressing privacy issues and implementing transparent practices.
- Integration and Ease of Use—Difficulty in incorporating GAI into current academic systems.
- Critical Thinking—Preventing GAI from diminishing analytical skills and deep understanding.
- Resource Constraints—Limited access to funding and quality datasets.
- Resistance to Change—Cultural and institutional pushback against new technologies.
- Regulatory & Compliance—Navigating complex legal requirements.

Faculty hurdles:

- Ethical Concerns—Addressing data privacy, GAI bias, and ensuring responsible use.
- Teaching Gaps—Insufficient training and varied familiarity with GAI among faculty.
- Resistance to Change—Reluctance to adopt new technologies that may disrupt teaching practices.
- Complex Implementation—Difficulties integrating GAI into established educational frameworks.
- Quality & Reliability—Concerns about the accuracy and reliability of GAI-generated content.
- Regulatory Compliance—Challenges in meeting data protection and compliance standards.

The above bullet points encapsulate the primary hurdles faced by both students and faculty in adopting GAI in education, highlighting ethical, technical, and institutional challenges. The researcher then identified common hurdles faced by both students and faculty to address the first study question. This was carried out by comparing the hurdles listed for each group and creating a Venn diagram to highlight overlapping challenges. In Figure 13, the diagram, featuring two circles representing students and professors, shows shared obstacles, providing a comprehensive view of the issues faced by both groups.

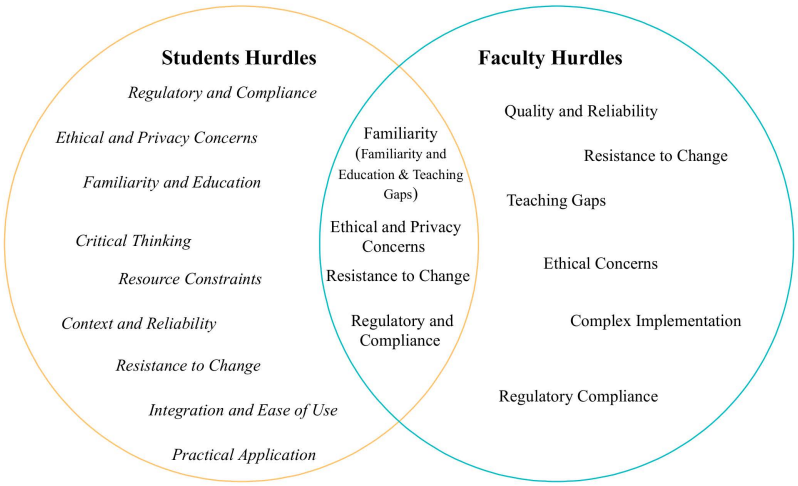


Figure 13. Venn diagram of faculty and student hurdles.

Figure 13 outlines the hurdles students and professors encounter when using GAI tools in academic settings. Students struggle with the need for familiarity, learning, practical application, and ensuring context and reliability. In the other side, faculty mem-

bers face difficulties bridging educational gaps, implementing complex GAI technologies, and maintaining quality and reliability while meeting strict regulatory standards. Both groups also deal with ethical concerns, resistance to change, and the need for regulation and compliance.

Figure 14 emphasizes that overcoming these hurdles is crucial for maximizing GAI's benefits while minimizing risks and ensuring effective adoption in academic and engineering contexts.

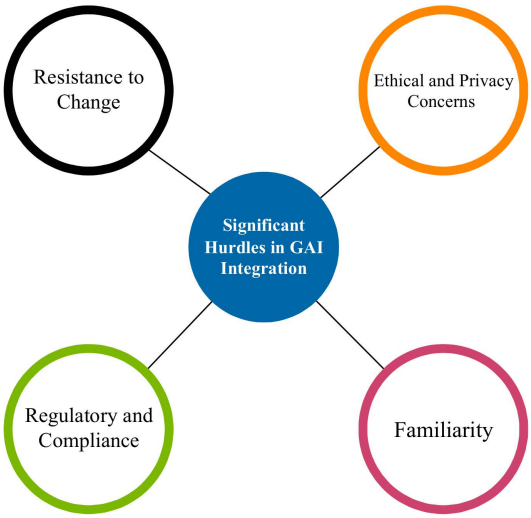


Figure 14. Key elements for successful GAI integration and implementation.

4.2. Prioritization of Factors: Expert Evaluation and Insights

In this section, this study conducted a survey at the American University of Sharjah (AUS) to gather feedback from students and faculty members, using separate questionnaires for each group. The student questionnaire had 49 questions across three sections, while the faculty questionnaire had 43 questions in three sections. Both surveys covered demographics, the potential of GAI technologies to enhance productivity in academia and engineering, and challenges in implementing GAI. Therefore, the Relative Importance Index (RII) will be used to evaluate the responses and identify key factors for educational institutions to consider when implementing GAI technology.

To clarify the analytical approach, the quantitative data collected in this stage were analyzed descriptively through frequency distributions and RII rankings. This approach aligns with the exploratory nature of this study, which aims to rank and prioritize adoption factors based on participants' perceptions rather than to test statistical associations or causal relationships. Descriptive and univariate analyses were thus selected to provide a transparent overview of response patterns and to contextualize participants' views identified earlier in the qualitative phase. While more advanced inferential analyses (e.g., correlations or regressions) could offer deeper insights into variable interdependencies, they fall beyond the scope of the present study, which seeks to establish early empirical evidence and identify key priorities for future investigation.

4.2.1. Students' Survey

The survey was conducted at the American University of Sharjah (AUS) on a randomly selected sample of 54 students. The sample included 23.6% of Graduates, 45.5% of Bachelor's students, and 30.9% of Master's students, with 56.4% females and 43.6% males. According to Table 6, students are divided across the university departments as follows: 63.6% in the College of Engineering; 18.2% in the College of Arts and Sciences;

14.5% in the School of Business Administration; and 3.6% in the College of Architecture, Arts, and Design.

Table 6. Demographic profile of Students.

Categories		Frequency
Degree of education	Graduates	23.6%
	Bachelors	45.5%
	Masters	30.9%
Department	College of Engineering	63.6%
	College of Arts and Science	18.2%
	School of Business Administration	14.5%
	College of Architecture, Art, and Design	3.6%
Gender	Females	56.4%
	Males	43.6%

Enhancing Student Productivity with GAI Tools

This study conducted a survey to assess the relationship between the use of GAI technology and productivity, focusing on a larger sample of students. One of the purposes of this survey was to evaluate students' familiarity with GAI technologies in academic and engineering contexts. It collected data on students' knowledge of generative AI tools by asking them to rate their understanding with the question, "How familiar are you with GAI techniques in engineering and academic disciplines?" The survey provided a brief explanation of GAI technology to guide their responses.

As seen in Figure 15, the survey results reveled that most students are familiar with GAI tools, with 74.1% rating themselves as "Moderately familiar" or higher. Only two students reported no familiarity at all, suggesting a widespread basic understanding of GAI tools. This knowledge base indicates a strong foundation for developing GAI-based educational programs to enhance productivity in various fields. The diversity in the applications of GAI, noted in the interview section, reflects the rapid innovation in the field, with different companies focusing on unique approaches. This ongoing growth provides opportunities to explore new advancements in generative AI.

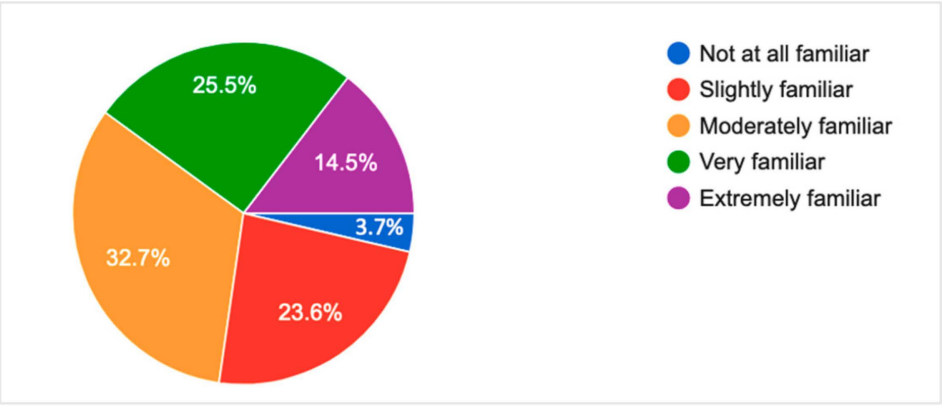


Figure 15. GAI familiarity level among the Students in Survey.

Figure 16 highlights ChatGPT and Bard as two of the most effective tools identified. Despite the brief period between the interview and survey, significant advancements, new tools, and increased competition in the AI space were observed. Given the rapid progress, the researcher plans to explore participants' knowledge of these updates in future studies.

According to the survey results, ChatGPT is the most popular tool among students, with 37 participants very familiar and 16 moderately familiar with it. GPT− 4 is the second

most popular, while tools like Scribe, AlphaCode, and Cohere Generate had significantly lower familiarity levels, with 38, 46, and 51 participants, respectively, being not very familiar. GitHub Copilot saw moderate familiarity, with 4 participants experienced and 8 slightly familiar.

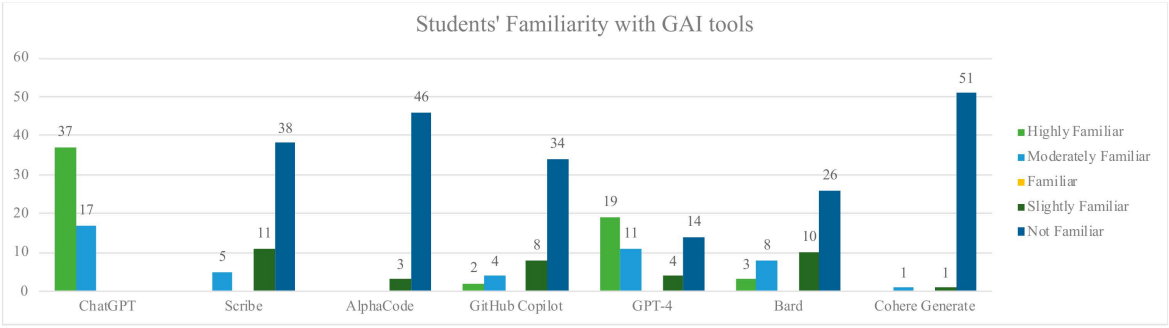


Figure 16. Students' familiarity with generative AI tools in the survey.

This study then highlighted a gap in knowledge and usage of various technologies, suggesting the need for better education to enhance their academic utility. Participants rated GAI tools' impact on productivity in five key areas, learning, research, problem-solving, project creation, and feedback, emphasizing their potential to boost academic performance as shown in Figure 17.

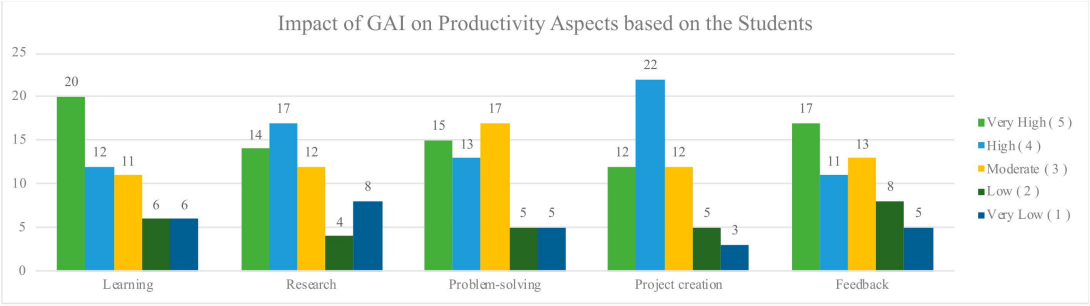


Figure 17. Impact of GAI on productivity aspects based on the student's survey.

The results exposed that majority of participants believed that GAI significantly enhanced their learning abilities, with most ratings being highly positive. For research, students also regarded GAI as an excellent tool, with strong ratings reflecting its usefulness. Opinions on problem-solving were more divided, with balanced scores indicating varied perspectives. The project creation aspect received favorable reviews, with students considering GAI beneficial in this area. Feedback was also positively viewed, showing its helpful influence. Overall, students expressed high confidence in GAI's potential to enhance productivity across learning, research, and project creation, though opinions on problem-solving differed.

In Figure 18, a concluding survey question confirmed GAI's perceived positive impact on students' academic success.

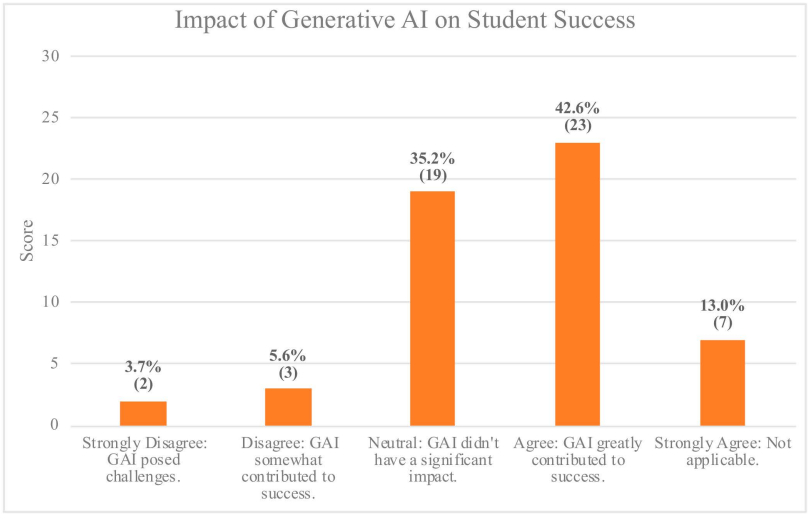


Figure 18. The impact of GAI on student success.

As shown in Figure 18, students' responses about the impact of the GAI on productivity varied widely. To begin, a small minority (3.7%) found it problematic, while 5.6% believed it had helped their success. Most students either felt it had no significant effect (35.2%) or thought it had contributed substantially to their success (42.6%). Additionally, 13% disagreed with the high approbation of the GAI. These findings indicated that students' experiences with GAI depended on factors such as ease of adaptation, organizational tools, and data analysis features, highlighting the diverse ways individuals had used this technology.

Student Factors for Successful GAI Integration

This section examines student survey data to determine critical characteristics that influence the adoption of GAI technology in educational institutions. Unlike interviews, which utilized a three-level rating system, the surveys used a more precise five-point scale ranging from "extremely important" to "not at all important," allowing for the development of a Relative Importance Index (RII). This index offered a clearer prioritization of difficulties and drove attempts to effectively integrate GAI technologies.

Figure 19a demonstrates that the RII results emphasize three essential student learning factors: adaptability to learning styles, interactive feedback, and content personalization. A significant requirement to accommodate individual learning preferences is evident from the 39 students who ranked "adaptability" as "very important" or "extremely important." Similarly, "interactive feedback" garnered good marks from 40 students, underlining its importance in improving the learning experience. At last, "content personalization" was identified as critical for customizing instructional content to different student demands. In Figure 19b, 16 and 18 students, respectively, rated "critical thinking stimulation" and "contextual understanding" as "extremely important" for implementing GAI in academic and engineering disciplines, making them the most significant factors in problem-solving contexts.

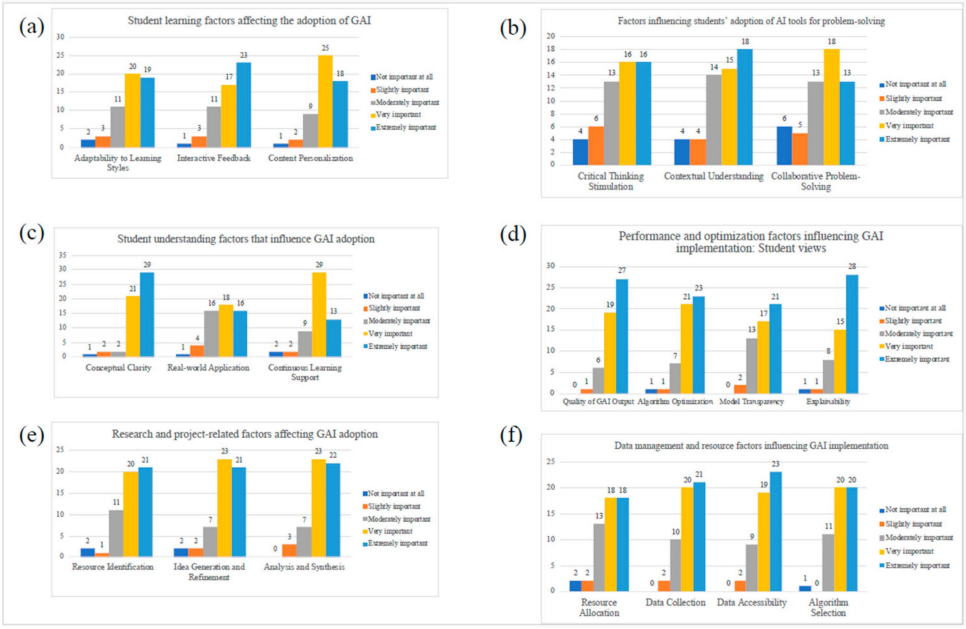


Figure 19. (**a**–**f**) Combined Insights on GAI in Engineering Education: (**a**) Student learning factors affecting the adoption of GAI tools; (**b**) Factors influencing students' adoption of AI tools for problem-solving; (**c**) Understanding factors influencing GAI implementation:; (**d**) Performance and optimization factors influencing GAI implementation; (**e**) Research and project-related factors affecting GAI adoption; (**f**) Data management and resource factors influencing GAI implementation.

As a result, our research results emphasize the necessity of creating an educational atmosphere that promotes critical thinking and allows for the practical application of theoretical information. Additionally, 13 students rated "collaboration in problem solving" as just somewhat significant. Likewise, as seen in Figure 19c, 29 students rated "conceptual clarity" as "extremely important," and 21 as "very important," making it the highest valued criteria.

According to these findings, GAI technology works best when applied in a collaborative learning environment to improve conceptual clarity, contextual awareness, and critical thinking. Additionally, the majority of students emphasized the need of integrating theory with real-world applications, as seen in Figure 19c, and "real-world application" was deemed crucial. A sustainable learning environment is crucial for continuing skill development, as evidenced by the high value placed on the aspect of "continuous learning support."

Based on Figure 19e and survey findings, students prioritized various characteristics that influence the effectiveness of GAI technology in research and projects. Three major project success factors emerged: resource identification (highly evaluated by 41 students), idea generation and refinement (44 students), and analysis and synthesis (45 students), emphasizing the relevance of resources, creativity, and critical thinking. The results also highlight how crucial resource and data management is to incorporating GAI technology, as seen in Figure 19f. Moreover, "Data accessibility" (23 votes) and "data collection" (21 votes) have been selected as the most important aspects for assuring GAI's efficacy in increasing student productivity. Furthermore, "algorithm selection" and "resource allocation" receive excellent ratings, indicating their relevance in performance optimization. With 27 votes affirming its critical importance, Figure 20a emphasizes that the "quality of GAI output" is the most crucial performance factor. Furthermore, "explainability" was identified as crucial, with 28 respondents highlighting the requirement for reliable and interpretable

data and 21 respondents emphasizing the need of model transparency for comprehending algorithms. 23 people agreed that algorithm optimization was significant.

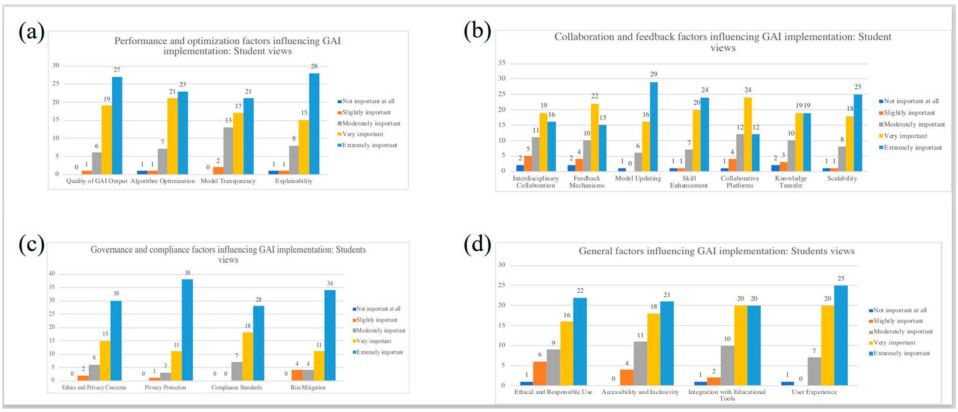


Figure 20. (**a**–**d**) Combined Insights on GAI Implementation in Engineering Education: (**a**) Performance and Optimization Factors; (**b**) Collaboration and Feedback Factors; (**c**) Governance and Compliance Factors; (**d**) General Influencing Factors, Student Perspectives.

In terms of collaboration and feedback, "model updating" was the top priority (29 responses), followed by skills enhancement (24 responses) and scalability (25 responses). These factors underscore the importance of interdisciplinary teamwork, skill development, and scalable technology adoption. Additionally, feedback mechanisms, interdisciplinary collaboration, and collaborative platforms were identified as essential for achieving optimal performance, as shown in Figure 20b.

The successful integration of GAI into engineering and academic fields is dependent on high-quality data, ongoing development, and effective cooperation. The survey's results highlight major issues about governance and compliance, including ethics, privacy concerns, and privacy protection. Figure 20c shows that 30 students ranked ethics and 38 rated privacy protection as "extremely important," whereas 28 and 34 students underlined the relevance of compliance standards and bias mitigation. In addition, Figure 20d shows that 16 students ranked ethical use and 18 students evaluated accessibility and inclusiveness as "very important." These findings together highlight overarching goals such as ethical and responsible use, accessibility and inclusion, seamless interaction with instructional resources, and improved user experience. According to these results of the student survey, the findings highlight the need for governance and compliance policies to ensure the ethical use of GAI.

Table 7 summarizes student votes on 35 factors, with RII values used to rank these factors in descending order of importance. The factors are classified based on RII values into categories: high (0.8–1), high-moderate (0.6–0.8), moderate (0.4–0.6), medium-low (0.2–0.4), and low (0–0.2), showing their relevance for improving academic and engineering performance with GAI technology. As mentioned in the RII Table below, the most important factor influencing students' expectations of adopting GAI technology in engineering and academic disciplines is privacy protection, with a rating of 0.925. It is followed by bias mitigation (0.883) and compliance standards (0.879), emphasizing the need for fair, accurate, and compliant results. Other key factors include model updating, ethics, privacy concerns, conceptual clarity, and quality of GAI output, all rated between 0.877 and 0.872. User experience, explainability, and skill enhancement are also significant, with ratings ranging from 0.857 to 0.845, highlighting the importance of ease of use, clarity, and skill improvement.

Table 7. Relative Importance Index (RII) of GAI Implementation: Results from Student.

Factors	Description	RII	Imp. Level
Privacy Protection	Keeping students' information safe and private when using GAI	0.925	H
Bias Mitigation	Finding and fixing any unfairness or mistakes that might happen with GAI	0.883	H
Compliance Standards	Making sure everything follows the rules and standards when using GAI	0.879	H
Model Updating	Letting GAI learn and become better with new information or feedback	0.877	H
Ethics and Privacy Concerns	Make sure generative AI respects privacy and follows the rules	0.875	H
Conceptual Clarity	Making complex ideas easy to understand	0.873	H
Quality of GAI Output	Ensure GAI results are accurate and helpful for learning	0.872	H
User Experience	The simplicity and satisfaction of using GAI tools.	0.857	H
Explainability	Being able to understand and explain the answers and things that GAI makes	0.857	H
Skill Enhancement	Learning new things and becoming better at using GAI for projects or research	0.845	H
Scalability	Making sure that GAI can handle more work as needed without problems	0.845	H
Algorithm Optimization	Making GAI work faster and better achieve goals	0.842	H
Data Accessibility	Being able to find and use different types of information easily with GAI	0.838	H
Analysis and Synthesis	GAI's ability to analyze data and summarize information for research and projects	0.833	H
Data Collection	High-quality data acquisition; Relevance assessment for GAI model training	0.826	H
Algorithm Selection	Choose the right GAI methods for the task at hand and ensure they are effective	0.823	H
Model Transparency	Understanding how GAI works and what it is doing	0.815	H
Idea Generation and Refinement	Using GAI to inspire creative ideas and improve research questions or project plans	0.815	H
Integration with Educational Tools	How well GAI fits with the current educational tools and platforms students use	0.811	H
Interactive Feedback	Giving quick and helpful feedback	0.811	H
Accessibility and Inclusivity	Ensuring GAI tools are usable by all students, including those with disabilities	0.807	H
Content Personalization	Customizing learning based on student progress and interests	0.807	H
Resource Identification	Helping students find useful resources for their projects	0.807	H
Ethical and Responsible Use	Teaching the ethical use of GAI, including avoiding bias and ensuring academic honesty	0.793	H-M
Knowledge Transfer	Sharing useful information and ideas with others using GAI	0.789	H-M
Adaptability to Learning Styles	Adapting content to fit how each student learns best	0.785	H-M
Resource Allocation	Funding availability; Access to GAI tools and infrastructure.	0.781	H-M
Continuous Learning Support	Supporting ongoing learning and understanding	0.778	H-M
Feedback Mechanisms	Asking students for their thoughts and ideas to make GAI better	0.766	H-M
Real-world Application	Showing how knowledge applies to real life	0.760	H-M
Interdisciplinary Collaboration	Working with students from different fields	0.758	H-M
Collaborative Platforms	Using shared tools or spaces online for working together with classmates	0.758	H-M
Contextual Understanding	Understanding and applying the context of problems	0.742	H-M
Critical Thinking Stimulation	Encouraging students to think critically.	0.724	H-M
Collaborative Problem-Solving	Helping students solve problems together	0.698	H-M

4.2.2. Faculty Survey

Table 8 shows a survey conducted to evaluate GAI's integration into engineering and academic disciplines, involving 42 faculty members from different academic roles at the American University of Sharjah (AUS), alongside a survey of AUS students.

The sample is primarily composed of PhD holders (69%), with 23.8% holding a master's and 7.1% possessing a bachelor's degree. In Figure 21a, the majority of participants (73.8%) are male and come from a variety of academic backgrounds, including engineering (28.6%), business administration (19%), architecture, arts, and design (14.3%), and arts and sciences (38.1%).

Table 8. Demographic profile of Faculty.

Categories		Frequency
Degree of education	Bachelors	7.1%
	Masters	23.8% 69%
	PhD	28.6% 38.1%
Department	College of Engineering	19%
	College of Arts and Science	14.3% 26.2% 73.8%
	School of Business Administration	
	College of Architecture, Art, and Design	
Gender	Females	
	Males	

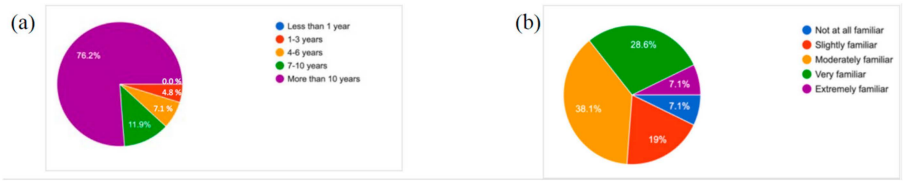


Figure 21. (**a**,**b**) (**a**) Years of Experience Among Faculty Members; (**b**) GAI Familiarity Levels Among Faculty Participants.

Also, a vast majority (76.2%) have more than ten years of academic experience, while smaller percentages have 7–10 years (11.9%), 4–6 years (7.1%), and 1–3 years (4.8%), with none less than one year. Thus, these demographics lay the groundwork for investigating how expertise and academic discipline influence the use of GAI tools in academia, particularly engineering.

Enhancing Faculty Productivity with GAI Tools

This study looks into how GAI can improve productivity among professors and academic personnel. Using a questionnaire, it evaluated faculty familiarity, application knowledge, and readiness to adopt GAI in education. Figure 21b illustrates that the results demonstrated a range of familiarity levels: 28.6% were very familiar, 38.1% moderately familiar, and 19% slightly familiar, with just 7.1% at the extremes (very familiar or not familiar at all). These data indicate that faculty are generally aware of GAI, emphasizing the necessity for institutions to provide seminars to improve comprehension and practical use in teaching and research.

Additionally, this study aimed to assess faculty understanding of specific GAI tools like Bard and GitHub Copilot. As shown in Figure 22, the results will help determine the depth of understanding and the potential applications of these tools in teaching, research, and service.

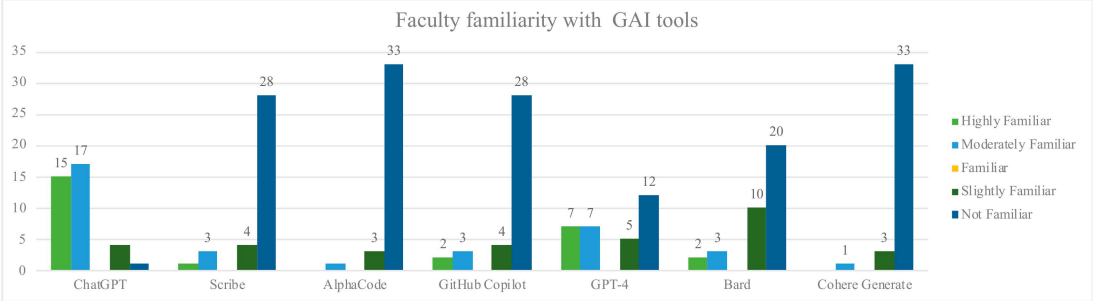


Figure 22. Faculty familiarity with Generative AI tools in the survey.

The results revealed that ChatGPT was the most well-known tool, with the majority of participants expressing strong familiarity, as shown in Figure 22. In contrast, tools such as AlphaCode and Cohere Generate were largely unfamiliar. Scribe and GitHub Copilot were moderately familiar, but GPT − 4 had a balanced level of experience among users. Overall, the findings highlight the need to raise knowledge of generative AI techniques in academic contexts.

Last, a survey question explored how GAI could enhance productivity in academic work, revealing faculty members' reactions and expectations regarding its use.

Based on Figure 23, reactions of participants to GAI technology varied widely, with ratings from 1 (Very Low) to 5 (Very High), showing overall engagement with its potential benefits. In teaching, 10 participants felt GAI could significantly improve productivity, while 7 gave lower estimates. On the other hand, higher ratings were also given for content creation and services, indicating a willingness to use GAI for productivity enhancement in these areas. Faculty generally agreed on GAI's potential, though individual differences and some reservations were noted. This highlights the need for further study to understand GAI's benefits and identify its appropriate academic applications.

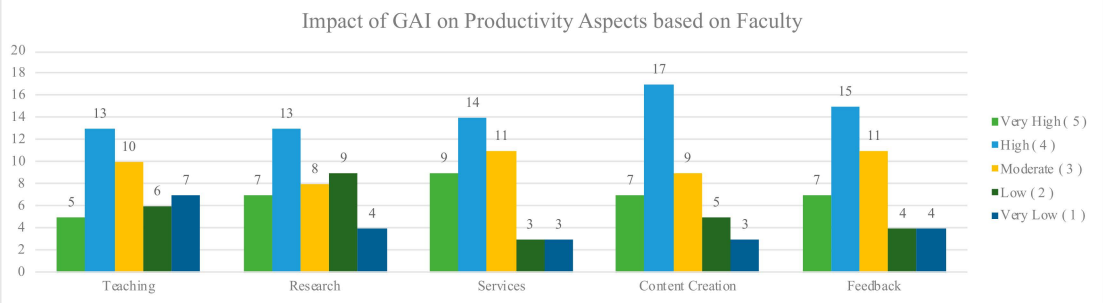


Figure 23. Impact of GAI on productivity aspects based on faculty survey.

Professors also discussed the challenges and opportunities of GAI in education, especially in teaching, revealing their views on its impact and potential barriers. Consequently, the results in Figure 24 showed that 9.8% of the sample strongly disagreed with GAI's relevance to their field, while 12.2% saw manageable challenges, and 31.7% were neutral, acknowledging modest issues but recognizing significant innovation potential.

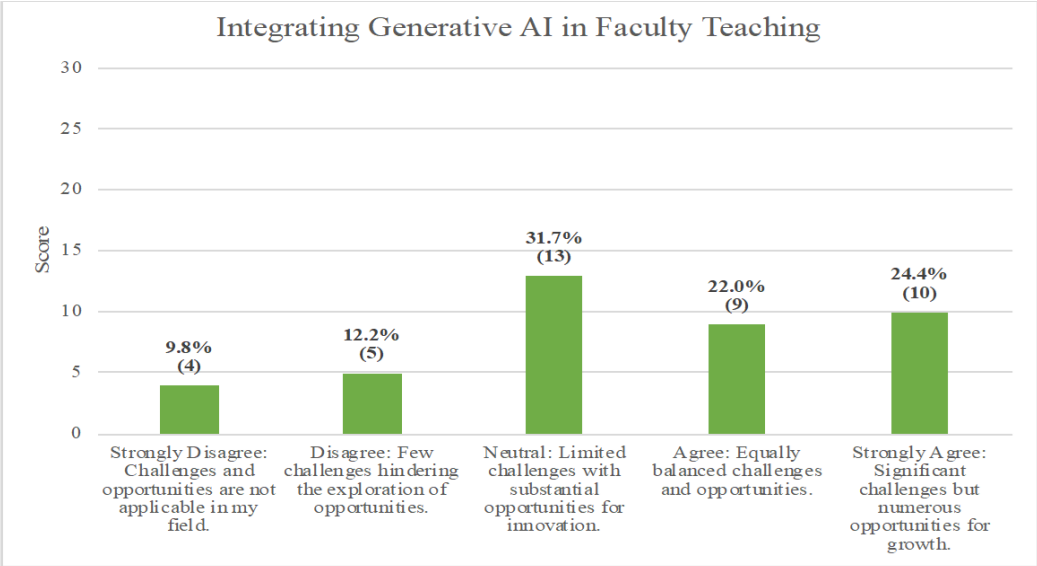


Figure 24. Integrating Generative AI in Faculty Teaching.

Most participants showed a positive outlook on the potential of GAI in education, with 22% seeing a balance between difficulties and opportunities, and 24.4% recognizing obstacles alongside possibilities for progress. This reflects differing views on GAI implementation, with a general optimism about its potential. Overall, a small percentage viewed the technology as irrelevant, suggesting a need for updates or new solutions.

Faculty Factors for Successful GAI Integration

Interviews with 13 faculty members, including professors and lab instructors, indicated significant factors impacting the use of GAI in engineering and academic disciplines. To strengthen these findings, this study will involve more faculty members and use the Relative Importance Index (RII) technique for a more thorough examination.

As shown in Figure 25a, "personalization and adaptivity" emerged as the most essential characteristics, with faculty emphasizing their role in personalizing learning experiences to specific student needs and fostering more effective education. In contrast, assessment automation and integrity sparked concerns, particularly about the fairness and accuracy of computerized evaluations. Furthermore, content accuracy and relevancy received good ratings, emphasizing the need of keeping educational materials current and credible. Collectively, these findings emphasize the necessity of tailored teaching approaches, cautious automation integration, and continual material updates in ensuring the effective and responsible use of GAI in educational settings.

Figure 25b depicts faculty members' assessments on the relevance of adopting Generative AI technology in this study's focal fields based on four major factors. Primarily, this study found that data analysis and idea generation are considered the most critical factors in the development of academic areas, with most participants rating them as very or extremely important. Idea generation and concept development were especially highlighted for their role in supporting innovation in academia and engineering. Dissemination and accessibility of research also received high ratings, demonstrating the significant impact a GAI could have in broadening access to information for researchers. Ethical and responsible research practices were given the highest priority, reflecting the understanding of the need for ethical adherence in both research and technology use.

It is evident from examining the findings of the faculty evaluation of service-related factors that the most crucial element for the effective use of GAI in academic and engineering fields was administrative efficiency, as demonstrated in Figure 25c.

Although they were deemed significant, service components including community engagement and outreach, professional development and communication were not viewed as being as crucial as other elements. Members prioritized these service factors while also stressing the importance of administrative efficiency.

In terms of performance and optimization, the quality of GAI output and explainability were the top priorities. 20 members rated the quality of output as "very important" or "extremely important," underlining the need for clear and accurate results. Additionally, 26 members highly valued explainability, highlighting the demand for easy-to-understand explanations of GAI outcomes. Figure 25d hig

The survey found conflicting views on "resource allocation" in relation to data and resource management. As seen in Figure 25e, 22 people ranked it as very or extremely important, whereas six participants thought it was not and slightly important. However, 28 participants rated "data collection" and "data accessibility" as extremely and vary important, underscoring the necessity of efficient data management and access in order to optimize the potential of GAI technology in the sectors under study.hlights the importance of model transparency and algorithm optimization, with positive feedback indicating their role in ensuring effective use of GAI in this study's core areas.

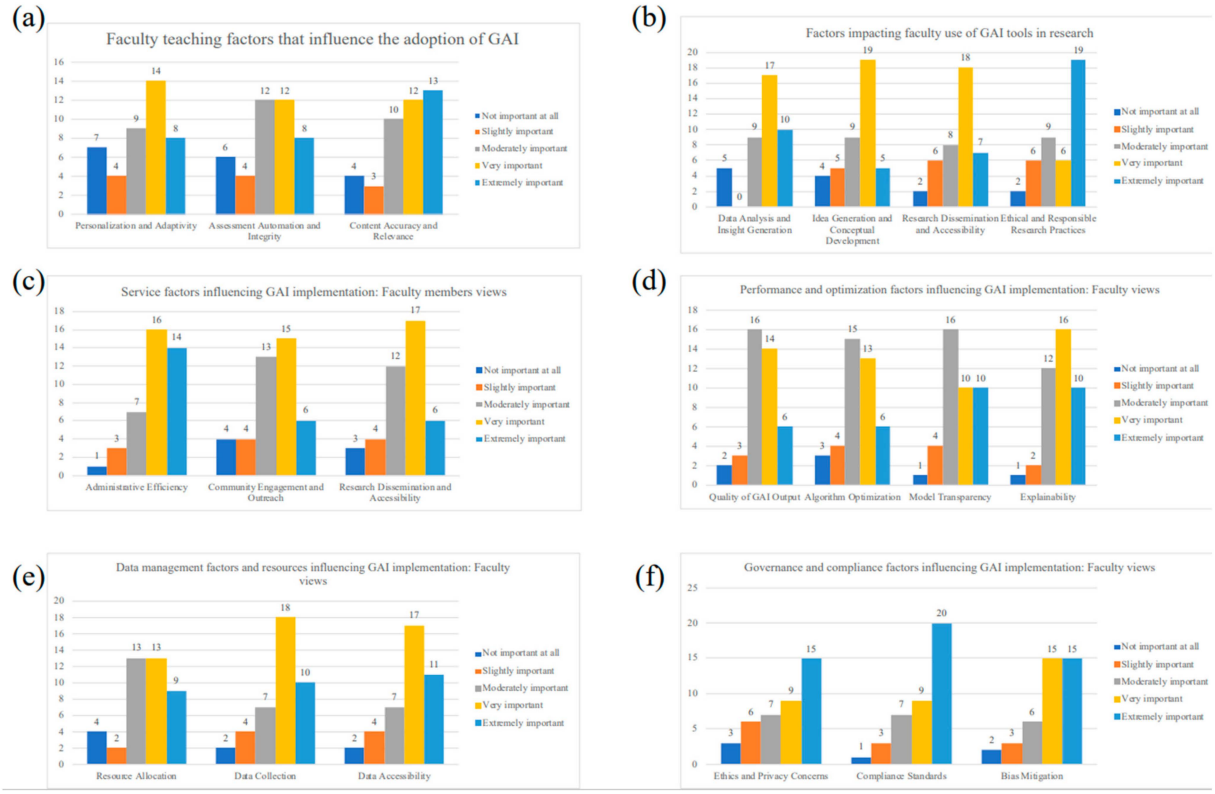


Figure 25. (**a**–**f**) Factors Influencing the Adoption and Implementation of GAI Tools from Faculty Perspectives: (**a**) Teaching Factors; (**b**) Research Factors; (**c**) Service-Related Factors; (**d**) Performance and Optimization; (**e**) Data Management and Resources; (**f**) Governance and Compliance.

Governance and compliance factors were also viewed as crucial (vary and extremely important), with 24 participants emphasizing the significance of ethics and privacy concerns. As shown in Figure 25f, "compliance standards" also were rated highly, with 29 participants deeming it very or extremely important, highlighting the significance of legal and ethical compliance in these applications. Finally, "bias mitigation" factor received a high rating, with 30 participants considering it important or extremely important. Therefore, these findings reflect academics' commitment to the importance of ethical and legal compliance in the use of technology.

Figure 26 depicts the results of combining the collaboration and feedback factors, which reflect variances in priorities. "Interdisciplinary collaboration" was rated as relatively important, with 24 participants highlighting its value. These results reflect academics' focus on the ethical, legal, and collaborative aspects of generative AI.

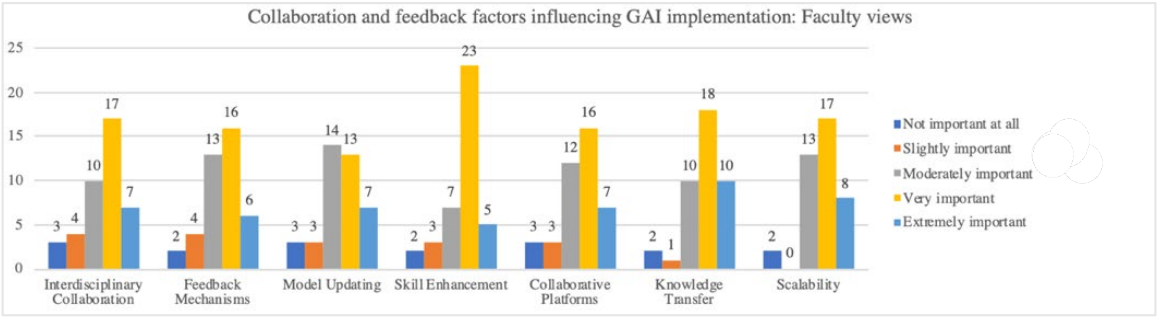


Figure 26. Collaboration and feedback factors influencing GAI implementation: Faculty views.

While "feedback mechanisms" and "model updating" also were received as highly important by 22 and 20 participants, respectively. "Skills enhancement" and "knowledge transfer" also received high ratings, with 5 and 10 participants viewing them as extremely important. These findings highlight the significance of capacity building and effective interdisciplinary cooperation for successful use of GAI technology.

Therefore, Table 9 summarizes the faculty members' votes on the 27 factors mentioned above, with the factors ranked in descending order of importance based on RII values.

Table 9. Relative Importance Index (RII) of GAI Implementation: Results from Faculty Members.

Factors	Description	RII	Imp. Level
Compliance Standards	Ensure generative AI use follows all rules and regulations in academic projects and research	0.820	H
Administrative Efficiency	Leveraging GAI for routine administrative tasks	0.790	H-M
Bias Mitigation	Use strategies to make generative AI fair for all students	0.785	H-M
Ethical and Responsible Research Practices	Ensuring ethical use of GAI in research	0.762	H-M
Knowledge Transfer	Best practices sharing; Insight's dissemination	0.761	H-M
Explainability	Ensure students can easily understand and use GAI results in their work	0.756	H-M
Data Accessibility	Make sure students can easily obtain the data they need	0.751	H-M
Data Collection	Look at how good data improves student learning and research	0.746	H-M
Scalability	Ensuring technology can grow with student needs	0.745	H-M
Ethics and Privacy Concerns	Address ethical issues and protect student privacy when using generative AI for learning and research	0.735	H-M
Data Analysis and Insight Generation	The capacity of GAI to process and analyse large datasets	0.732	H-M
Skill Enhancement	Training resources availability; Skill development programs	0.730	H-M
Content Accuracy and Relevance	Keeping GAI-generated content up-to-date	0.729	H-M
Model Transparency	Make sure everyone understands how GAI models work	0.717	H-M
Research Dissemination and Accessibility	Making research easy to understand and access	0.707	H-M
Resource Allocation	Check if students have enough tools and resources to use GAI	0.702	H-M
Interdisciplinary Collaboration	Helping different fields work together	0.702	H-M
Collaborative Platforms	Using tools for teamwork between students and faculty with GAI	0.702	H-M
Feedback Mechanisms	User feedback collection; Continuous improvement loops	0.698	H-M
Quality of GAI Output	Measure how well GAI helps students learn and understand concepts	0.693	H-M
Professional Development and Networking	Helping faculty find and connect with relevant professional growth opportunities and events	0.690	H-M
Model Updating	Continuous learning mechanisms; Adaptation to new data and feedback	0.690	H-M
Idea Generation and Conceptual Development	Creating new research ideas with GAI	0.676	H-M
Algorithm Optimization	See how better GAI algorithms can improve student work and grades	0.673	H-M
Community Engagement and Outreach	Using GAI to understand and meet community needs through targeted programs	0.671	H-M
Personalization and Adaptivity	Tailoring learning to each student's needs and styles	0.657	H-M
Assessment Automation and Integrity	Automating grading fairly with GAI	0.657	H-M

To successfully integrate GAI technology into engineering and academic disciplines, three key factors must be addressed: compliance with academic norms and rules (RII = 0.820), administrative efficiency through task automation (RII = 0.790), and the application of bias mitigation techniques for equity and inclusion (RII = 0.785). Ethical research practices (RII = 0.762) and faculty support for knowledge transfer (RII = 0.761) are also essential for creating an environment conducive to responsible use and understanding of GAI. When coordinated, these factors will enhance the long-term integration of GAI to boost productivity in these areas.

4.2.3. Summary of Stage 2

This paper explores the application of GAI technology in engineering and academic disciplines, focusing on how it is used by students and professors. Survey results show no clear agreement on the factors influencing its use by both groups. While instructors seek to improve and simplify the educational process for students, students primarily aim to use GAI technology to accelerate their academic progress and graduate quickly. In Figure 27, the researcher suggests analyzing the impact of these factors using metaphorical forces and proposes a force field analysis to identify key factors that influence both groups, addressing the second research question.

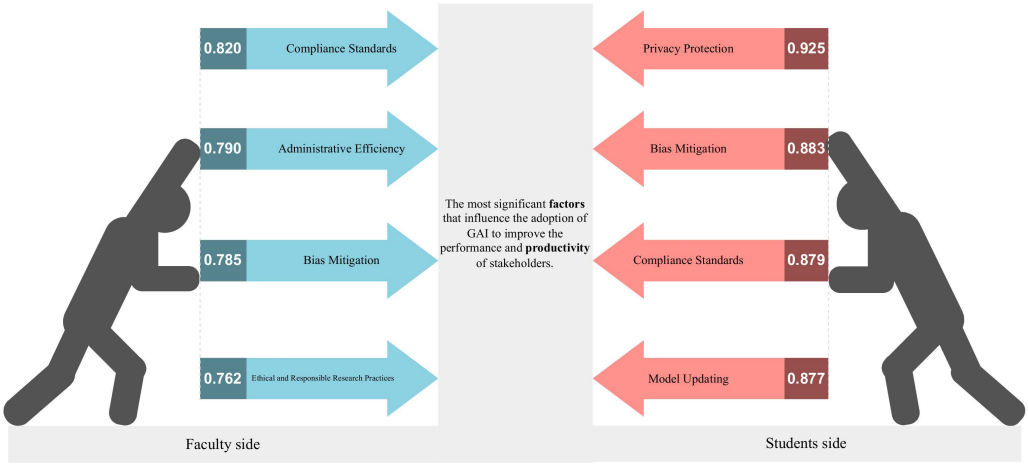


Figure 27. Force Field Analysis Diagram for Student and Faculty Factors.

In this analysis, the researcher used a force diagram based on RII tables from students and faculty to identify common factors related to the integration of GAI technology in education. It is clear that the compliance standards and bis mitigation factors are presented in two sets of factors. However, the force field analysis was found to be insufficient for answering the research question and did not provide a complete view of the educational impact factors. As a result, the researcher turned to a mind map, considered a more effective approach.

In Figure 28, this mind map identifies key factors influencing the use of GAI to enhance performance and productivity, with the central question guiding the exploration.

To explain further, the central question is divided into three categories: faculty factors, student factors, and educational impact. Faculty factors emphasize compliance, ethics, and minimizing biases in GAI use. The first branch, Faculty Factors, emphasize compliance, ethics, and minimizing biases in GAI use. While Student Factors focus on privacy, GAI quality, equitable outcomes, and secure data processing. Finally, highlights GAI's potential to improve learning through tailored materials and interactive feedback.

These factors collectively form a framework for analyzing the implementation of GAI, applicable across organizations to boost productivity. The chapter concludes that the hurdles and factors align with previous literature, underscoring GAI's role in enhancing productivity for students and faculty in academia and engineering.



Figure 28. Mind Map of Factors Influencing the Use of GAI in Most Organizations.

5. Discussion, Conclusions, Limitations, and Future Directions

This study critically examined the integration of GAI technologies in engineering education, focusing on productivity enhancement for students and faculty. Through a multi-method approach, literature review, semi-structured interviews, and structured surveys, this research offers both theoretical insights and empirical evidence about GAI's transformative potential and its associated challenges while also highlighting its role in advancing sustainable engineering education and supporting the United Nations Sustainable Development Goals (SDGs).

The findings confirm that GAI technologies, including ChatGPT, Bard, and natural language processing tools, hold significant promise for reshaping engineering education and academic workflows. Faculty interviews and survey data revealed a broad consensus that GAI can streamline labor-intensive tasks such as grading, course material generation, and data analysis. Students emphasized GAI's potential to support adaptive learning, project development, and critical thinking enhancement by automating routine tasks and providing immediate feedback. Interestingly, both groups recognized GAI's ability to handle large datasets and facilitate complex engineering design and modeling tasks, thus bridging the gap between theoretical concepts and practical applications in ways that also foster sustainable design practices and responsible innovation.

However, this study also revealed substantial challenges that hinder the seamless adoption of GAI. Resistance to change was evident, especially among faculty, who expressed concerns about potential disruptions to established educational practices and the risk of diminishing human creativity and critical thinking. Concerns about ethical compliance, algorithmic bias, data privacy, and model transparency emerged as significant barriers. Faculty highlighted the importance of robust governance frameworks and comprehensive training to address these challenges. From the students' perspective, issues of GAI tool reliability, data accuracy, and uneven access to resources were underscored as impediments to optimal integration. These barriers point to the need for governance structures that embed sustainability principles such as equity, inclusivity, and ethical responsibility into GAI-enabled learning environments.

A particularly noteworthy result is the variation in familiarity and comfort with GAI across engineering disciplines. Contrary to assumptions of uniform digital literacy, the data demonstrated significant disparities in GAI knowledge and usage even within the same academic programs. For instance, while computer and electrical engineering students reported advanced familiarity and proactive engagement with GAI, students from civil and mechanical engineering exhibited more cautious and limited use. This finding underscores the necessity for tailored educational interventions that account for disciplinary differences and individual learning needs, ensuring that GAI integration contributes to equitable and sustainable learning outcomes across fields.

Furthermore, the data revealed divergent perspectives on GAI's role in education. Students viewed GAI as a tool to enhance academic success, creativity, and efficiency, emphasizing immediate benefits such as faster assignment completion and innovative project design. In contrast, faculty were more focused on the long-term implications, such as safeguarding academic integrity, maintaining high educational standards, and ensuring compliance with ethical norms. These contrasting views highlight the need for a balanced approach to GAI integration that addresses both groups' priorities and aligns with sustainability goals that promote innovation without compromising ethics, inclusivity, or long-term educational quality.

An unexpected insight from the interviews was the informal use of GAI technologies by both students and faculty, even in the absence of formal institutional policies. This indicates strong underlying demand and suggests that institutions must act swiftly to establish governance structures, training programs, and support mechanisms to harness GAI's potential while mitigating associated risks. Embedding sustainability principles, such as responsible use of resources, ethical governance, and alignment with SDG 4 (Quality Education) and SDG 9 (Industry, Innovation, and Infrastructure), will be critical in guiding this integration.

This study provides a comprehensive framework for understanding the integration of GAI technologies in engineering education. By identifying key factors influencing adoption, such as technical infrastructure, ethical compliance, user training, and interdisciplinary collaboration, it offers actionable insights for stakeholders aiming to enhance productivity and learning outcomes while simultaneously advancing sustainable development in higher education.

This research highlights that GAI is not merely an incremental addition to educational tools but represents a potential paradigm shift in the way learning, research, and administrative processes are conducted. When strategically integrated, GAI can enhance creativity, improve operational efficiency, and support innovation in engineering education. However, its adoption must be accompanied by robust ethical safeguards, tailored training, and thoughtful governance to ensure equitable and responsible use. In this sense, GAI can serve as both a driver of productivity and a catalyst for sustainable engineering education, preparing future engineers to contribute effectively to global sustainability challenges.

While this study provides rich insights, several limitations should be acknowledged. First, this research was conducted within a single institution, which may limit the generalizability of the findings to other academic or industrial contexts. Second, the sample size, though carefully selected, may not fully capture the diversity of perspectives across institutions or regions. Third, the focus on engineering disciplines, while justified, excludes potentially valuable insights from other academic domains such as the humanities, social sciences, and business. Finally, the quantitative analysis relied on perception-based data examined descriptively through the RII, which effectively captures the relative prioritization of factors but does not explore interrelationships among variables. Future studies could therefore complement this approach with inferential statistical techniques, including non-

parametric tests (e.g., Mann–Whitney U, Kruskal–Wallis), correlation analysis, or structural equation modeling (SEM), to assess associations, validate group differences, and enhance the robustness of the findings. Nonetheless, the present analytical approach remains methodologically appropriate for this study's exploratory objectives and provides a strong empirical foundation for more advanced confirmatory investigations in future research.

Building on the insights from this study, several promising directions emerge for future research. First, scholars could expand disciplinary coverage to include fields such as healthcare, finance, the arts, and social sciences, thereby assessing the broader applicability and impact of GAI integration beyond engineering. Increasing sample diversity and institutional scope would also enhance the robustness and generalizability of findings across regions. In addition, longitudinal studies are needed to capture the long-term effects of GAI on productivity, learning outcomes, and professional competencies, moving beyond early adoption stages. Future investigations may also develop discipline-specific GAI tools aligned with pedagogical and ethical goals, while exploring policy frameworks and governance models that ensure responsible, equitable, and sustainable integration. Finally, advancing interdisciplinary collaboration will be essential for bridging knowledge gaps and fostering innovation across diverse academic domains.

The findings of this study also provide actionable implications for higher education institutions and policymakers. Institutions should establish clear ethical guidelines for GAI use, addressing issues such as bias, privacy, and transparency, and invest in digital capacity building to strengthen faculty and student competencies. Facilitating cross-disciplinary collaboration and creating feedback-driven learning platforms will allow universities to adapt dynamically to evolving GAI technologies. Moreover, embedding sustainability principles into training programs and curricula can ensure that GAI adoption supports responsible innovation, equitable access, and long-term educational resilience.

This study highlights GAI's transformative potential in engineering education while emphasizing the need for strategic, ethical, and inclusive integration. By addressing both technical and human factors, institutions can harness GAI to drive productivity, creativity, and academic excellence while also advancing sustainable education and contributing to SDGs such as Quality Education, Innovation, and Responsible Consumption.

Beyond the immediate institutional context, the findings hold broader implications for curriculum development, professional training, and higher-education policy. The integration of GAI calls for curricular redesign that embeds digital literacy, ethical reasoning, and sustainability awareness across engineering programs, ensuring that graduates are equipped for data-driven and AI-augmented workplaces. Similarly, faculty development initiatives should extend beyond basic tool training to include pedagogical adaptation, assessment redesign, and strategies for guiding students in the responsible use of GAI. At the policy level, the results underscore the importance of establishing institution-wide governance frameworks and national guidelines that balance innovation with academic integrity, equity, and long-term resilience. Making these dimensions explicit reinforces this study's practical significance for educators, administrators, and policymakers seeking to align technological transformation with sustainable educational practice.

Finally, while this study focuses primarily on the integration of GAI within engineering education, its implications extend well beyond academia. The insights drawn from students' and faculty members' experiences can inform strategies for diverse organizations, ranging from government agencies to private enterprises, seeking to harness the potential of these technologies responsibly. As GAI continues to evolve, it is reshaping how we interact with information by transforming static data into dynamic, adaptive insights. This paradigm shift mirrors broader technological disruptions observed across sectors, from the digitization of media to the automation of industrial operations. A critical question

thus emerges: will GAI remain a supportive tool that enhances human productivity and creativity, or will it fundamentally redefine the landscape of academic and professional work? By addressing the ethical, technical, and pedagogical challenges identified in this study, institutions and organizations alike can position themselves at the forefront of this transformation, ensuring that GAI complements human ingenuity and contributes to a more sustainable and equitable future.

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