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“THE IMPACT OF ARTIFICIAL INTELLIGENCE ON HIGHER EDUCATION”

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Preface

This first volume of the Society of North American Scholars (SNAS) interdisciplinary conference proceedings highlights the high-quality research and some intellectual contributions of our attendees. The SNAS Board initiated this publication as a testament to the organization's commitment to academic excellence and as a platform to showcase the valuable work presented at our conference.

The 3rd Annual Interdisciplinary Conference, held on October 11, 2024, at Western Connecticut State University in Danbury, Connecticut, focused on *The Impact of Artificial Intelligence on Higher Education*. This theme is timely and critical as AI technologies continue shaping various sectors, notably higher education. The conference provided an essential forum for scholars, educators, administrators, and technology experts to examine how AI transforms teaching, learning, research, and institutional operations.

The Organizing Committee invited participants to submit 3-to 5-page summaries of their presentations to establish a formal conference record. These summaries underwent an editorial review. Each contribution reflects the growing impact of AI on education and the innovative approaches being developed to harness its potential.

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Abstract: *Advancements in technology are transforming education and integrating academic and socio-emotional development. AI-powered adaptive learning platforms can enhance social and emotional learning (SEL) by personalizing instruction, fostering emotional intelligence, and improving interpersonal skills. While research has focused on AI's cognitive benefits, its role in SEL remains underexplored. This paper examines how coding apps and AI promote SEL and digital citizenship, using CodeMonkey as a case study. It highlights how AI features can support SEL initiatives, demonstrating their potential to enhance students' emotional intelligence and responsible digital behavior.*

Introduction

As technology rapidly advances, schools are increasingly integrating AI-powered platforms to create dynamic learning environments that support the holistic development of students. These platforms improve academic outcomes and offer opportunities to cultivate critical social and emotional skills. Social-emotional learning (SEL) includes self-awareness, self-regulation, empathy, and interpersonal relationships, which are crucial for students' success in both school and life. However, there is a notable lack of research on the role of AI and coding tools in promoting these skills. This paper aims to bridge this gap by examining how AI-powered platforms like CodeMonkey can enhance SEL and digital citizenship. The significance of SEL has been widely recognized, particularly following the COVID-19 pandemic, when global organizations like UNESCO advocated for integrating SEL into digital learning to support sustainable and peaceful societies.

Traditional Social and Emotional Learning (SEL) methods versus AI-powered SEL Tools

Traditional Social and Emotional Learning (SEL) methods and AI-powered SEL tools differ significantly in delivery, personalization, feedback, and scalability. Traditional SEL methods rely on direct human interaction, structured curricula, and manual assessments. While this personal connection is valuable, it is resource-intensive and lacks scalability. Research shows that traditional SEL programs often fall short due to limited session durations, lack of consistency in implementation, and primarily qualitative, subjective assessments. Additionally, tailoring SEL to individual student needs is challenging due to time and resource constraints.

In contrast, AI-powered SEL tools, such as virtual reality (VR) environments, wearable devices, and chatbots, offer innovative approaches to emotional skill development. These technologies can use natural language processing (NLP) and machine learning to provide personalized emotional support, empathetic dialogues, and tailored interventions. However, despite their potential, these technologies present challenges such as high costs, the need for staff training, and unequal access, which could deepen the digital divide.

CodeMonkey, a digital platform initially designed to teach coding, has expanded to include SEL and digital citizenship courses. Compared to traditional SEL methods and more expensive AI-powered devices, CodeMonkey is more affordable, accessible, and engaging. Its interactive nature and gamified elements make learning enjoyable and effective, encouraging students to apply SEL skills in real-life situations. Furthermore, the platform provides teachers with detailed insights into student performance, enabling them to create targeted lesson plans based on real-time data.

The platform's digitalization of SEL content streamlines data collection and analysis, saving teachers time and allowing them to focus more on direct student interaction. CodeMonkey's affordability and robust security measures make it accessible and safe for a broader range of educational institutions, offering a promising solution for modernizing SEL education. Integrating SEL into a familiar and engaging digital platform, CodeMonkey prepares students for academic success and responsible digital citizenship in today's technology-driven world.

Discussion

To enhance student engagement and the effectiveness of Social-Emotional Learning (SEL) in CodeMonkey's Digital Citizenship minicourses, the paper proposes several improvements centered on AI technologies such as NPL integration and Progress Tracking. Firstly, the paper suggests that the courses incorporate Natural Language Processing (NLP) to create immersive, AI-driven challenges. These would place students in real-world scenarios, such as handling cyberbullying and fostering engagement, empathy, and cooperative learning. Secondly, Progress Tracking can be a valuable tool to be implemented for real-time progress tracking. By incorporating AI-driven behavioral analytics, student interactions and emotional responses can be monitored, enabling personalized feedback and adaptive learning experiences. Finally, the paper underlines the value of gamification with rewards and recognition that would boost student motivation. Personalized, dynamic reward systems would make the learning experience more engaging and tailored to individual needs. These AI enhancements are strongly believed to make CodeMonkey's SEL courses more interactive, adaptive, and impactful for students.

Conclusion

Education must adapt to the evolving technological landscape in the post-pandemic era by incorporating advanced tools supporting academic and socio-emotional development. AI-powered platforms, like CodeMonkey, offer promising solutions for modernizing SEL education and promoting responsible digital citizenship. These platforms can provide personalized, engaging, and efficient learning experiences by leveraging AI's capabilities. Gamification and a well-structured reward and progress-tracking system can be implemented into the mini-courses, increasing enjoyment and a positive learning experience. Recognizing and rewarding achievements motivates students and helps them internalize SEL skills, fostering a growth mindset and resilience. Thus, the paper underscored the importance of integrating AI into SEL education to better prepare students for the complexities of the digital world while safeguarding their privacy and well-being.

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INTEGRATING AI INTO CAPSTONE DESIGN PROJECTS: ENHANCING ENGINEERING EDUCATION AND PREPARING STUDENTS FOR THE AI-DRIVEN FUTURE

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Abstract: *Generative AI transforms engineering education by enhancing design processes, fostering innovation, and preparing students for an AI-driven future. This study explores the integration of AI tools, such as ChatGPT and Gemini, across a three-semester Engineering Design course. AI supports concept generation, design analysis, and manufacturing, improving efficiency and decision-making. Ethical considerations, including privacy, bias, and intellectual property, are also examined. Results show that AI enhances creativity and critical thinking, positioning it as an essential tool in engineering education. As AI adoption grows, balancing its benefits with traditional learning methods will be key to fostering responsible and effective engineering practices.*

Introduction

Engineering education is rapidly evolving, driven by technological advancements. As an educator in the *Engineering Design* course, I have firsthand experience with the profound changes emerging from integrating generative AI tools such as ChatGPT, Gemini, and similar platforms. This transformation enhances learning outcomes and prepares students for the AI-driven future of engineering. This presentation discusses how incorporating generative AI across a three-semester design project sequence fosters innovation, efficiency, and critical thinking among engineering students and some ethical and practical considerations.

Course Structure and Curriculum Overview

The course *Engineering Design* serves as the foundation for a three-semester design sequence. The structure is heavily inspired by the *Engineering Design Process* curriculum by Yousef Haik and Tamer Shahin, which emphasizes systematic problem-solving and creativity. The sequence is divided into three stages:

First Semester: Engineering Design Fundamentals

The first stage introduces students to essential design principles, where they explore customer needs, market analysis, and conceptual design development. Drawing inspiration from chapters like *Identifying Needs and Gathering Information* and *Developing Concepts*, students apply methods such as brainstorming, creating function trees, and developing morphological charts to generate innovative ideas. Generative AI tools, such as ChatGPT, have become invaluable at this stage by assisting students with idea generation, market research, and even the creation of detailed design briefs and conceptual designs.

Second Semester: Capstone Project—Design and Analysis

The second stage focuses on detailed project planning, including sketching, drawing, and analyzing proposed designs. The curriculum covers topics such as embodiment design, analysis, and prototyping. Generative AI has proven particularly useful for assisting students in evaluating design alternatives and performing simulations and analysis. In many instances, AI-supported tools simplified tasks like structural analysis or helped refine material selection, improving the process's efficiency and allowing students to focus on higher-level design considerations.

Third Semester: Capstone Project—Manufacturing and Prototyping

In the final stage, students take their designs through the prototyping and manufacturing phases. While traditional tools and methods are essential here, AI integration continues to assist in areas such as cost analysis, selection of manufacturing methods, and ensuring the designs comply with standards and codes. AI’s capacity to streamline these processes has made it an indispensable tool for both students and educators.

The Role of Generative AI in Engineering Education

Integrating generative AI tools into the engineering curriculum has transformed how students engage with the design process. Skepticism about AI's impact on learning was present, especially in a field that demands both technical rigor and creativity. However, as teaching progressed, it became evident that these tools enhance student capabilities rather than replace critical thinking.

AI in Concept Generation and Design Thinking

In the first semester, students are often tasked with creating multiple design alternatives and sketching preliminary ideas. Traditionally, this is a time-intensive process that involves trial and error. Generative AI, however, accelerates concept development by offering immediate feedback on feasibility, generating alternative solutions, and even suggesting innovative combinations of functions. Students are not limited to their own imaginations—they can use AI to explore ideas beyond their initial scope.

This parallels the historical introduction of the calculator in education, where it first served as a supplementary tool and eventually became essential in classrooms. AI is similarly positioned to become indispensable in engineering education, with foundational knowledge built upon and enhanced by AI capabilities.

AI in Analysis and Evaluation

By the second semester, the focus shifts to detailed design and analysis, where AI proves even more valuable. For instance, tools like Gemini and ChatGPT have supported students in performing stress analysis and optimizing designs based on material properties and environmental considerations. These AI tools allow students to quickly evaluate design alternatives and make informed decisions, leading to significant improvements in the quality and efficiency of student work.

AI has also been instrumental in guiding students through ethical evaluations, helping them consider standards, codes, and societal impacts during their design phases. AI-driven insights into sustainability and safety considerations ensure that students develop designs that are both innovative and compliant with industry requirements.

Ethical and Practical Considerations

Addressing privacy, data security, bias, intellectual property, and resource limitations. Ethical training and balancing AI use with traditional engineering principles

The current research addresses several ethical, social, and cultural concerns related to the use of AI models. Ethically, there are worries about privacy violations, data protection, and intellectual property, as AI systems may collect personal data without consent, generate biased or discriminatory content, and raise questions about the ownership of AI-generated work. Concerns about reliability and over-reliance on AI are also mentioned, with fears that inaccurate texts and diminished human creativity could hinder learning. Socially, the lack of human interaction in AI systems may impact students' social and emotional skills, while issues of affordability and accessibility create disparities in access to AI resources. Culturally, AI's lack of cultural sensitivity and failure to account for socioeconomic diversity is highlighted, as AI-generated content may not respect linguistic and cultural nuances or represent diverse backgrounds adequately. Here is the

Summary of Ethical Concerns

- *Privacy and Data Protection:* There are several concerns about AI models violating users' privacy by collecting and storing personal data without consent. The risk of data leaks and misuse was highlighted as a major issue.
- *Bias and Discrimination:* Some are anxious that AI models will reflect societal biases, potentially leading to discriminatory or offensive content that could affect learning outcomes.
- *Intellectual Property:* Concerns were raised about the ownership of AI-generated content and the potential for plagiarism, questioning the originality and creativity of AI-assisted work.
- *Reliability of Texts:* The accuracy and relevance of AI-generated texts are questioned, with factual errors and irrelevant content being noted.
- *Reliance on AI Models:* There are concerns that students' overreliance on AI could diminish their human interaction, creativity, and critical thinking skills.

Summary of Social Concerns

- *Human Interaction:* The absence of human elements in AI interactions is seen as a drawback, potentially impacting students' social skills and emotional intelligence.
- *Affordability and Access:* The high cost of reliable AI models limits accessibility, raising concerns about equitable access to AI resources.
- *Inclusivity and Equity:* AI models may favor users in developed regions with better access, exacerbating disparities among students globally.

Summary of Cultural Concerns

- *Cultural Sensitivity:* AI models sometimes generate culturally insensitive content, failing to respect linguistic diversity and cultural nuances.
- *Socioeconomic Diversity:* The data used by AI models may not adequately represent diverse socioeconomic backgrounds, affecting the inclusivity of AI-generated content.

Outcomes and Future Implications

The results of integrating generative AI into the classroom have been overwhelmingly positive. Students report increased confidence in their abilities to tackle complex design challenges, and their final projects exhibit a level of sophistication that often exceeds initial expectations. More importantly, AI fosters a culture of iterative design thinking, where students use it not just for answers but to explore possibilities and refine their solutions continuously. Generative AI is a game-changer in engineering education, much like the calculator was decades ago. While its use may not completely replace traditional methods of learning and problem-solving, it undoubtedly enhances them. As with the calculator, there is likely to be a gradual shift where knowledge builds on AI-based tools, and students become adept at leveraging these technologies for more advanced problem-solving. In time, we may see AI becoming the cornerstone of engineering education, driving innovation and expanding the boundaries of what students can achieve.

Conclusion

The introduction of generative AI into the *Engineering Design* course has fundamentally reshaped how students approach the design process, from concept generation to detailed analysis. As educators, we guide this transition, ensuring that AI becomes an enabler of creativity and critical thinking rather than a crutch. Looking forward, the role of AI in engineering education is not just promising but essential. As we refine how we integrate AI into curricula, it will likely become the standard, driving educational excellence and engineering innovation.

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ASSESSING ARTIFICIAL INTELLIGENCE'S TRANSFORMATIVE IMPACT ON HIGHER EDUCATION

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Abstract: *This study explores the transformative impact of Artificial Intelligence (AI) on higher education, examining its influence on teaching, research, and administration. A comprehensive survey investigates AI tool usage (ChatGPT, Gemini, Bing, etc.) among students, faculty, and staff, assessing usage frequency, perceived impact on academic performance, and user proficiency. Preliminary results, primarily from computer and information science participants, reveal ChatGPT as the most popular tool (33% usage), with 85% of users reporting improved performance. Concerns regarding academic integrity (31%) and lack of regulation (27%) were prominent. The study highlights the need for institutional support, including ethical training and regulatory guidance, to effectively integrate AI while addressing challenges like bias and ensuring responsible implementation.*

Research Motivation

Artificial Intelligence (AI) profoundly reshapes higher education, impacting teaching methods, research activities, and administrative operations. This study briefly examines AI's transformative effects, focusing on both the positive outcomes and the challenges it presents within academic environments. A comprehensive questionnaire has been developed to collect detailed insights from various academic participants, including students, faculty, administrative staff, etc.

Table 1.

Most frequently used AI platforms

Company	***AI Tool Name***	***Information***
Open AI https://openai.com/	ChatGPT	ChatGPT: An AI language model developed by OpenAI, capable of generating human-like text based on the input it receives. ChatGPT-2: Improved version with enhanced text generation capabilities, offering better coherence over longer conversations. ChatGPT-3: Features a larger model size and improved contextual understanding, enabling more detailed and accurate responses. ChatGPT-4: Latest iteration with further advancements in understanding and generating nuanced and contextually relevant text.
	Dall-E	DALL-E: An AI model by OpenAI that generates digital images from textual descriptions, displaying creativity and a grasp of complex attributes. DALL-E 2: Enhanced version with better image resolution, more realistic image generation, and the ability to edit parts of generated images or create variations.
Google https://gemini.google.com/app	Gemini	Google Gemini: A generative AI model developed by Google, designed to manage both text and image modalities. It integrates

		different forms of media input to produce coherent multimedia content, blending capabilities typically seen in models like GPT (text) and DALL-E (images).
Grammarly Inc. https://www.grammarly.com/	Grammarly	Grammarly: A digital writing assistance tool that uses AI to improve spelling, grammar, punctuation, clarity, engagement, and delivery in text. It provides suggestions and corrections in real-time, helping users enhance their written communication across various platforms and document types.
Facebook https://ai.meta.com/	Meta AI	Meta AI: An initiative by Meta Platforms (formerly Facebook) focusing on advancing AI technology across various applications. This includes development in natural language processing, computer vision, and more, aimed at enhancing user experiences on social media platforms and beyond.
Microsoft https://www.bing.com/chat	Bing/Copilot	Bing: A web search engine from Microsoft that provides a variety of search services, including web, video, image, and map search capabilities. It uses AI to enhance search relevance and user interaction features. Copilot: An AI-powered coding assistant developed by GitHub and OpenAI. It assists developers by suggesting code completions and snippets in real-time, based on the context of the existing code, helping to improve productivity and code quality.
Anthropic https://claude.ai	Claude	Claude AI: Developed by Anthropic, Claude AI is a conversational AI model focused on safety and usability. It is designed to generate coherent and context-aware responses in dialogues, emphasizing ethical guidelines and user-friendly interactions.

Key Contributions

Many people depend heavily on AI tools to complete their assignments or personal work, significantly impacting the learning and development of creative skills. The survey primarily investigates the variety and frequency of AI tool usage across educational institutions, focusing on platforms such as ChatGPT, Gemini, Bing, Grammarly, Meta AI, DALL-E, Claude, etc. It evaluates how these technologies influence academic performance and the degree of trust users have in them.

Additionally, the questionnaire measures the proficiency levels of users, ranging from beginners to experts, and identifies their primary challenges. These include issues like high costs, insufficient regulatory frameworks, and concerns regarding academic integrity.

The survey also explores the types of institutional support participants find necessary for effective AI integration. This includes the need for ethical training workshops, seminars on regulatory guidance, and adequate technological support. Furthermore, the questionnaire explores how AI is utilized to enhance personalized learning experiences, increase research productivity, and assist in overcoming challenges faced by disadvantaged groups within the academic community. All responses are collected anonymously to ensure privacy and encourage honest feedback, which is crucial for the accuracy and relevance of the findings.

Preliminary Results

Our survey, which predominantly involved participants from computer science and information science departments, revealed distinct patterns in the adoption and impact of generative AI tools. ChatGPT emerged as the most utilized tool, with approximately 33% of respondents indicating its use, while only 6% reported using Claude.

Regarding usage frequency, 40% of the respondents indicated they sometimes use these tools, while 25% or 20% reported frequent or widespread usage. Notably, 85% of participants observed improved performance using AI tools. The survey also examined trust in AI technologies. Positive attitudes were reported by 45% of respondents, whereas 55% expressed neutral opinions. Moreover, 50% of users were familiar with AI tool functionalities, though 5% had never used them. From a regulatory perspective, 42% of respondents expected more institutional support to learn about AI regulations, and 32% suggested that institutions should host workshops on ethical AI usage.

31% of respondents highlighted challenges associated with AI implementation, particularly those concerning academic integrity. 27% cited the lack of adequate regulations. Additionally, 15% felt uninformed about effective AI utilization.

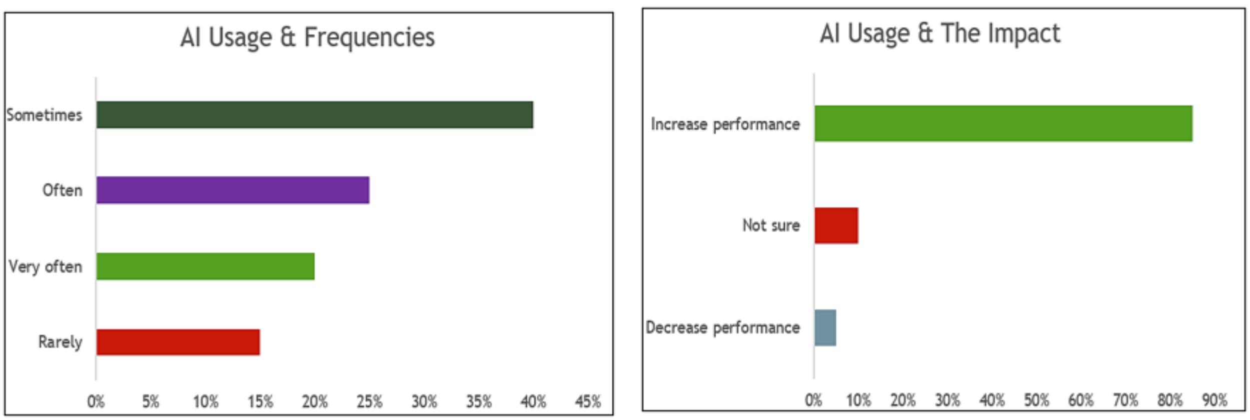

Figure 1 . AI usage frequency and impact

Concerns about the negative implications of AI on academic integrity were significant, with 45% fearing potential violations. However, 40% believed that AI use would not adversely affect their careers. Regarding employment prospects, 40% anticipated no negative impact, whereas 25% expressed concerns about job market changes due to AI advancements.

55% of the respondents recognized bias within AI models as a critical issue. This concern is prevalent not only among scientists but also among the broader community of AI users.

Implications

The data obtained through this study is expected to illuminate the current integration of AI tools in educational settings and highlight their practical implications for the stakeholders involved.

The anticipated results will provide vital data to help shape strategies to maximize AI's benefits in education while addressing the associated challenges. This abstract serves as an introduction for conference attendees interested in AI's transformative role in higher education.

Considering these insights, our findings support comprehensive training for all AI users to ensure a thorough understanding of the technology's background, limitations, regulations, and methods for obtaining accurate, unbiased information.

EXPLORING THE ROLE OF AI FOR CLIMATE CHANGE MITIGATION THROUGH CARBON FARMING

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Abstract: *Climate change threatens global agriculture, necessitating innovative solutions like carbon farming. Practices such as no-till, cover cropping, and biochar application enhance soil carbon sequestration, but their effectiveness depends on advanced monitoring tools. This study explores the role of artificial intelligence (AI) in optimizing carbon farming and improving both carbon storage and agricultural productivity. AI-driven strategies reduce emissions and enhance efficiency while addressing socio-economic challenges. Ethical, accessible AI solutions are essential for inclusive sustainability. Ultimately, AI-integrated carbon farming presents a viable path toward climate resilience, requiring global collaboration to maximize its potential in mitigating climate change and ensuring food security.*

Introduction

Climate change poses a significant challenge to the agricultural sector, which plays a dual role as both a major source of global greenhouse gas (GHG) emissions and a key player in efforts to reduce them. Agriculture is responsible for about 24% of global GHG emissions, mainly due to methane from livestock and nitrous oxide from fertilized soils (IPCC, 2019). Nevertheless, carbon farming offers a promising solution for mitigating climate change by using farming practices that boost soil organic carbon (SOC) levels while cutting emissions (Lal, 2018). Techniques like no-till farming, applying biochar, and using cover crops help lower emissions, improve soil health, increase water retention, and support biodiversity.

AI is a rapidly evolving technology that offers a unique opportunity to enhance carbon farming efforts. Farmers can access real-time information about soil conditions, crop health, and carbon capture potential using AI tools like precision agriculture, automated data analysis, and predictive modeling. This technology can significantly improve the efficiency of carbon farming, making it easier to scale up carbon sequestration projects. This paper examines how AI can drive advancements in carbon farming and strengthen climate resilience in agriculture. It also emphasizes the importance of global collaboration and policy support in encouraging the adoption of AI-based sustainable farming practices (GIZ, 2024).

Methodology

This study employs a systematic literature review to examine the integration of Artificial Intelligence (AI) in carbon farming practices, aiming to provide a comprehensive overview of AI's role in optimizing soil carbon sequestration, improving agricultural productivity, and enhancing climate resilience.

A structured literature search was conducted across electronic databases, including Web of Science, Scopus, Google Scholar, and ResearchGate. Keywords such as "AI in carbon farming," "carbon sequestration with AI," "no-till farming and AI," and "biochar application and AI" guided the search process. To ensure the relevance and currency of the findings, the review focused on English-language publications dated from 2010 to 2024.

Studies were included if they directly discussed the application of AI in carbon farming or similar agricultural practices, evaluated AI's impact on soil carbon sequestration, soil health, crop productivity, or water management, and were published in peer-reviewed journals or by reputable institutions. Excluded studies were those focusing solely on conventional farming practices without incorporating AI elements, those lacking empirical data, and publications outside the designated timeframe or language criteria.

Relevant information was systematically extracted for each selected study, including the type of AI technology used (e.g., machine learning, remote sensing, big data analytics), the specific carbon farming techniques assessed (e.g., no-till farming, cover cropping, and biochar application), and key findings on the effectiveness of these technologies. This data was organized thematically to enable a clear comparison and focused analysis.

The collected data was categorized into key themes reflecting the primary areas of AI integration in carbon farming: optimization of carbon sequestration, resource efficiency, sustainability benefits, and socio-economic implications. This thematic organization allowed for an in-depth analysis of AI's contributions to each area within the context of carbon farming.

This study synthesizes findings from existing research to identify AI's potential and limitations in carbon farming. It provides insights into technological advancements and socio-economic barriers to adopting AI in sustainable agricultural practices.

Results

Integrating AI into carbon farming presents several promising outcomes across soil carbon sequestration, resource use efficiency, and agricultural sustainability. Carbon Sequestration Optimization: AI-driven technologies have shown significant potential in enhancing soil carbon storage. Techniques such as no-till farming, cover cropping, and biochar application benefit from AI tools that provide real-time insights into soil conditions, enabling farmers to make precise adjustments to planting depth, seeding rates, and soil treatments. For example, AI-enabled drone and sensor systems used in the Midwest United States reported a 15%

increase in soil carbon retention through optimized tillage depth, demonstrating AI's effectiveness in enhancing carbon storage while reducing greenhouse gas emissions (Smith et al., 2020).

Resource Efficiency: AI applications have also proven effective in managing critical resources such as water and nutrients. In water-scarce regions like Gujarat, India, AI-integrated closed-loop irrigation systems reduced water use by 30% and improved soil carbon retention by 20% (Gatla, 2019). Such systems help farmers make data-driven irrigation decisions, conserving water and optimizing its application. Similarly, AI-powered tools facilitate precision fertilization and pest control, minimizing resource waste and enhancing the overall sustainability of farming practices (Delgado et al., 2019).

Sustainability and Socio-economic Impact: The broader implications of AI in carbon farming extend beyond environmental benefits to include socio-economic gains (Grunwald, 2022). By increasing productivity and lowering input costs, AI makes sustainable practices more economically viable for small-scale farmers, particularly in regions with limited resources. AI-supported platforms accessible through mobile applications provide affordable precision farming solutions, enabling farmers to monitor soil health and make informed decisions that improve yields (Galaz et al., 2021; Shaikh et al., 2022). Additionally, the adoption of AI-driven systems fosters inclusive development, helping to address disparities in agricultural knowledge and technology access (GIZ, 2024).

Case Studies: Practical implementations of AI in carbon farming further demonstrate its impact. In the United States, AI-powered satellite imagery and sensor systems have been used to monitor soil carbon levels, allowing timely adjustments to farming practices (Paul et al., 2023). In Kenya, an AI-driven early crop failure detection system utilizing satellite images and soil sensors has enhanced resilience to climate change and improved food security for local farmers (Demenois et al., 2020). In Ghana, an AI-based pest and disease identification system for cashew crops has reduced losses and increased productivity (GIZ, 2024).

Overall, the results indicate that AI-driven carbon farming practices contribute meaningfully to climate resilience, carbon sequestration, and sustainable agriculture.

These findings underscore AI's role as a transformative tool in optimizing carbon farming practices and supporting socio-economic growth within agricultural communities.

Conclusion

Integrating AI into carbon farming offers a promising solution to climate change while promoting sustainable agricultural practices. Through AI, farmers can enhance carbon sequestration, improve resource efficiency, and boost crop yields, creating both environmental and socio-economic benefits, particularly for small-scale farmers in areas with limited resources. Nevertheless, fully realizing AI's advantages requires addressing challenges related to cost, accessibility, and technical skills. With strong collaboration and support from governments, research bodies, and the private sector, AI has the potential to significantly advance resilient and sustainable agricultural systems, contributing meaningfully to global climate goals.

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COSCHOLAR: A RETRIEVAL-AUGMENTED GENERATIVE AI APPLICATION FOR LITERATURE REVIEW SYNTHESIS

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Abstract: *The rapid expansion of academic literature necessitates advanced tools for efficient literature review synthesis. Coscholar, a retrieval-augmented generative AI application, aids researchers by integrating large language models with retrieval techniques to mitigate AI hallucination. It processes up to 40 full-text studies, extracting key elements to ensure accurate synthesis. Using a multi-model approach, it categorizes themes, evaluates research, and identifies trends. Its retrieval-based framework enhances factual consistency and traceability. With an interactive interface, researchers can customize analysis depth and style, making Coscholar a versatile tool for streamlining literature reviews while maintaining academic integrity.*

Introduction

The increasing complexity and volume of academic literature have motivated researchers to explore integrating artificial intelligence (AI) tools into scholarly work. In recent years, generative AI has emerged as a promising solution to assist researchers by streamlining the literature review process (Brown et al., 2020). The ability of large language models (LLMs) to generate human-like text has been harnessed for various academic tasks, including summarization, translation, and question-answering. However, the "AI hallucination" phenomenon has been a persistent challenge — generating plausible yet inaccurate information (Bender, Gebru, McMillan-Major, & Mitchell, 2021). In response, retrieval-augmented generation (RAG) approaches have been developed to ground generated content in verifiable data sources, thereby improving reliability and relevance (Lewis et al., 2020). Recent advances—including integrating reinforcement learning from human feedback—have further improved factual consistency in generated outputs (Bai et al., 2022; OpenAI, 2023). Moreover, recent journal articles have begun to address the practical and ethical challenges associated with applying these models in academic contexts (Chakravarthi, 2022; Sun, Hu, & Wang, 2023). This paper introduces Coscholar, a novel application explicitly designed to support academic researchers by synthesizing and summarizing research findings across multiple studies, with the additional aim of reducing the time and effort required for literature review drafting.

Literature Review

The past few years have seen an evolving discussion around the application of generative AI in academic research, with several studies focusing on both the opportunities and risks inherent in these technologies. Recent research has examined the integration of LLMs into academic workflows, particularly for tasks such as automated summarization and the synthesis of scholarly content (OpenAI, 2023). A key debate has centered on the reliability of LLM-generated content. Researchers have expressed concerns that without appropriate grounding in source data, even state-of-the-art models may produce text that is not sufficiently accurate for academic purposes (Bender et al., 2021).

Emerging studies have begun to address these issues through hybrid approaches that combine retrieval systems with generative models. For example, the retrieval-augmented generation framework proposed by Lewis et al. (2020) has demonstrated that integrating a retrieval module can significantly improve the factual correctness of generated content. Additional research has also examined post-2022 enhancements to these methods. For instance, Chakravarthi (2022) provides an in-depth analysis of how retrieval augmentation can mitigate hallucinations in text generation, while Sun, Hu, and Wang (2023) discuss best practices for integrating these methods into scholarly research to ensure both transparency and academic rigor. Overall, while the literature indicates promising advances in the use of generative AI for research synthesis, there remains a call for applications that are finely tuned to the rigorous demands of academic writing.

Description of the Coscholar Application

Coscholar is a generative AI application designed to assist academic researchers in drafting the literature review sections of their research projects. The application leverages an RAG approach to ensure that outputs are firmly anchored in the source material provided by the researcher. Unlike conventional generative models that rely on pre-trained, generalized knowledge bases, Coscholar ingests up to 40 full-text studies and systematically processes them by extracting individual research questions, methodologies, results, and conclusions. This preprocessing step ensures that the subsequent synthesis is both precise and contextually relevant.

A core feature of Coscholar is its multi-model architecture. The system analyzes diverse aspects of academic texts by employing several state-of-the-art LLMs, including thematic categorization and critical evaluation. The application first dissects each study's contributions and then uses an aggregation algorithm to identify overarching themes, debates, and gaps in the literature. This methodology enables researchers to quickly gain insights into current research trends and theoretical frameworks, thereby reducing the traditionally time-consuming process of manual literature review.

Furthermore, the integration of retrieval-based techniques minimizes the risk of AI hallucination. Every piece of synthesized text is traceable to an input study, and

The system is configured to flag inconsistencies or unsupported claims. Such traceability is crucial for academic integrity, allowing researchers to verify the provenance of the generated content easily. Coscholar's user interface is designed for interactivity. Researchers can input studies, adjust parameters for synthesis (such as depth of analysis or focus on specific themes), and even experiment with different narrative styles. This flexibility ensures that the application can adapt to the diverse needs of academic disciplines while maintaining adherence to scholarly conventions.

Conclusion and Recommendations

The rapid evolution of generative AI presents significant opportunities and challenges for academic research. Coscholar exemplifies a promising direction by integrating retrieval-augmented generation to produce reliable and contextually grounded literature reviews. The application demonstrates that by combining multiple LLMs with robust data retrieval mechanisms, researchers can substantially reduce the time they spend on literature synthesis while upholding the accuracy and academic integrity of the review process.

Looking ahead, it is recommended that future research continue to refine RAG-based applications with a particular focus on transparency and traceability of the generated content. Academic publishers and research institutions should consider collaborating to develop standardized frameworks for evaluating the reliability of AI-assisted literature reviews. Furthermore, interdisciplinary efforts are needed to address the ethical implications and potential biases in generative AI outputs. As the body of work in this domain grows, continued empirical studies and peer-reviewed research will be essential to validate these tools in diverse academic settings and to ensure that generative AI contributes positively to scholarly communication (Bai et al., 2022; Chakravarthi, 2022; Sun, Hu, & Wang, 2023; OpenAI, 2023).

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CAN ONE COUNT ON AI?

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Abstract: *Artificial Intelligence (AI) is becoming ubiquitous, making its reliability a concern for everyone. AI is prone to industry failures despite its potential, as seen in IBM Watson's oncology errors, AI-driven ball-tracking mishaps in sports, and fatal autonomous vehicle accidents. Key challenges include data biases, lack of interpretability, ethical risks, hallucinations, misinformation, and environmental impact. Ensuring responsible AI deployment requires rigorous data validation, bias mitigation, ethical oversight, and human intervention. This research explores AI's limitations and proposes strategies to enhance reliability across critical healthcare, sports, and transportation sectors. It also aims to question the reliability of AI tools in a broad, inclusive manner, emphasizing their impact on all individuals, regardless of profession, community, or location.*

Striking Failure Examples

For instance, IBM Watson's failure in oncology services at Memorial Sloan Kettering Cancer Center highlights the pitfalls of AI development. Despite a $62 million investment, the AI system provided unsafe and incorrect treatment suggestions due to limited data sets and reliance on hypothetical cases. This led to misdiagnosis and poor data quality, which are common issues in AI failures. They might have achieved better results if IBM had focused on real-world medical variables and broader data sets. It is crucial to understand the limitations of AI when using it in critical fields such as healthcare.

The second example is from the use of AI in sports: AI-powered technology has the potential to revolutionize the sports industry, and one promising area is camera handling, where AI-driven ball-tracking technology can streamline manual tracking tasks for human camera operators and reduce costs for streaming services. However, as Inverness Caledonian Thistle FC demonstrated in October 2020, AI can still encounter challenges. Their intelligent camera operator, designed to track the ball using convolutional neural networks, failed to distinguish between the ball and the lineman's bald head. This error, caused by similarities between the objects and a specific camera angle, resulted in an unsatisfactory viewing experience for fans. Despite this setback, the potential benefits of AI-driven ball-tracking technology remain significant. Automating camera movements can improve the quality and efficiency of sports broadcasts, making them more accessible and enjoyable for viewers.

The last example is from transportation with many cases: While autonomous vehicles (AVs) promise safer, more efficient transportation, their potential risks cannot be ignored. A notable instance is the fatal accident involving an Uber self-driving car in 2018. This incident and other studies suggest that AVs may be more prone to accidents than traditional vehicles. The Uber crash highlights the challenges of AI in real-world driving conditions. Despite technological advancements, AVs struggle to perceive and respond to their environment accurately. In the Uber case, a delay in the system's response to a pedestrian contributed to the fatal outcome. These incidents underscore the importance of robust testing, rigorous safety standards, and continuous improvement in AV development. Prioritizing user experience over safety can lead to unintended consequences, as demonstrated by Uber's oversight in programming for split-second crashes.

Why does AI Fail?

Highlighting several other unarguable failures of AI leads us to the main reasons behind such failures. Questioning the reliability of AI tools results in listing the main pitfalls and shortcomings of AI, including—but not limited to—bias, lack of originality, hallucinations, ethical concerns, environmental impact, dependency on data quality, and limited understanding. More instances of AI failures from the real world highlight the failures of AI tools more thoroughly.

As evidence, the reliability of AI is a multifaceted challenge. While AI has made remarkable strides, it is essential to approach its capabilities critically.

1) AI systems are trained on vast amounts of data, and their reliability heavily depends on the quality and diversity of this data.
    - AI can amplify biases in the training data, leading to unreliable and potentially harmful outcomes.
    - AI models can be susceptible to adversarial attacks, where malicious actors manipulate inputs to produce incorrect outputs.
2) The algorithms that run big data themselves are ill-designed.
3) The complexity of many AI systems and intense learning models makes them challenging to understand and interpret. This lack of transparency can hinder our ability to identify and rectify errors.

Although efforts focus on improving data quality, developing robust AI models, and implementing rigorous testing and evaluation procedures, perfect reliability might be an unattainable goal. A human-in-the-loop approach, where humans oversee and correct AI decisions, can help mitigate risks and improve overall system performance.

Limitations of AI

In addition, generative AI tools have gained momentum in popularity and are being widely used, but there are certain limitations due to

- ***Lack of originality:*** These models excel at generating content similar to what they have been trained on but struggle with genuinely novel ideas or creative breakthroughs.
- ***Bias:*** AI models inherit biases from the data on which they are trained. This can lead to discriminatory or unfair outputs.
- ***Hallucinations:*** Generative AI can produce plausible-sounding but incorrect or nonsensical information, often called "hallucinations."
- ***Ethical concerns:*** Misuse of generative AI can create deepfakes, misinformation, and other harmful content.
- ***Environmental impact:*** Training large language models requires vast energy and resources, contributing to environmental concerns.
- ***Dependency on data quality:*** The quality and diversity of the training data directly affect the output quality.
- ***Limited understanding:*** While AI can process information and generate human-like text, it lacks a proper understanding of the world and the context of the information it processes.

Addressing these shortcomings requires ongoing research, development, ethical guidelines, and regulations.

To provide a comprehensive understanding of AI's limitations, I have carefully selected prominent examples of failures, both historical and contemporary. Additionally, I have drawn upon my experiences with generative AI tools, highlighting the challenges and pitfalls I have encountered firsthand. To further contextualize the current state of AI, I have analyzed its position within the Gartner Hype Cycle, examining the industry's expectations and the reality of AI's capabilities. Finally, based on my observations and insights, I offer a set of recommendations that are essential for all AI users to consider, regardless of their level of expertise or the specific application of AI in their work.

How to Minimize Potential Shortcomings of AI?

Given the pervasive integration of AI into various industries worldwide, my recommendations have the potential to significantly enhance the effectiveness and reliability of AI applications, especially in critical sectors such as healthcare, where even minor errors can have severe consequences. Here is a summary of key considerations to be cautious against the shortcomings of AI:

Data Quality and Quantity

- ***Data Quality:*** Ensure your data is clean, accurate, and representative of the problem you are trying to solve. Outliers, inconsistencies, and biases can significantly impact AI performance.
- ***Data Quantity:*** Sufficient data is essential for AI models to learn patterns and generalize effectively. A lack of data can lead to underfitting.

Model Selection and Architecture

- ***Model Complexity:*** Choose a model appropriate for your problem's complexity. Overly complex models can lead to overfitting, while simpler models might not capture subtle patterns.
- ***Hyperparameter Tuning:*** *To optimize model performance, e*xperiment with different hyperparameters (e.g., learning rate, batch size).

Bias and Fairness

- ***Bias Detection:*** Be aware of potential biases in your data and models. Use bias detection tools and fairness metrics to identify and mitigate biases.
- ***Fairness Interventions:*** Implement strategies to ensure your AI system treats different groups fairly. This might involve adjusting data, algorithms, or decision-making processes.

Interpretability and Explainability

- ***Model Interpretability:*** Understand how your model makes decisions. This can help identify potential biases and errors.

- ***Explainable AI:*** Use techniques like feature importance, SHAP values, or LIME to explain the model's predictions.

Ethical Considerations

- ***Privacy and Security:*** Protect user data and ensure compliance with relevant regulations.
- ***Accountability:*** Establish mechanisms for accountability and transparency in AI systems.
- ***Societal Impact:*** Consider the potential consequences of AI on society, including job displacement, privacy concerns, and ethical implications.

Continuous Learning and Improvement

- ***Feedback Loops:*** Incorporate feedback mechanisms to improve your AI system continuously.
- ***Retraining:*** Regularly retrain your model with new data to adapt to changing conditions.

One can help mitigate the potential shortcomings of AI and ensure that it is used effectively and responsibly by carefully considering these factors.

ADVANCING MENTAL HEALTH CARE THROUGH AI AND INTERDISCIPLINARY EFFORTS IN HIGHER EDUCATION

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Abstract: *Artificial Intelligence (AI) is revolutionizing mental health care by enhancing early detection, diagnosis, and treatment of conditions such as postpartum depression (PPD). Machine learning models, natural language processing, and neural networks analyze speech, facial expressions, and social media behavior to identify patterns, enabling personalized treatment plans and continuous patient monitoring. Our research focuses on the interdisciplinary development of AI tools for PPD prediction, addressing the maternal mental health studies gap. By integrating expertise from healthcare, technology, and ethics, we aim to improve predictive accuracy, clinical utility, and accessibility of AI-driven mental health solutions within higher education and beyond.*

Research Motivation

Recent advances in Artificial Intelligence (AI) and technology have shown great potential for real-life applications that promote social good. AI in mental health is transforming the approach to diagnosing, treating, and monitoring mental disorders. Related technologies, such as machine learning models, natural language processing, and neural networks, analyze large datasets to identify patterns that may not be apparent to humans. This capability enables the early detection of conditions like depression or anxiety through analysis of speech patterns, facial expressions, and social media behavior. AI-driven tools also personalize treatment plans by predicting individual responses to various therapies, and they support continuous monitoring of patients' mental health through wearable devices and mobile apps. The integration of AI aims to enhance the efficacy, accessibility, and customization of mental health services. Higher education institutions play a vital role in these advancements, as interdisciplinary collaboration within these settings can drive the development of practical AI solutions for mental health.

Effective management and treatment of complex mental health issues such as anxiety, depression, post-traumatic stress disorder (PTSD), obsessive-compulsive disorder (OCD), bipolar disorder, and postpartum depression (PPD) necessitate collaborative efforts. Interdisciplinary cooperation, bringing together diverse expertise, is crucial for developing comprehensive approaches. Despite the complexity of these conditions, research often remains siloed within specific disciplines, missing the benefits of a multidisciplinary approach.

Recent scholarly activities have increasingly focused on leveraging AI to address complex healthcare challenges within the realm of mental health. A significant study by Saqib, Khan, and Butt in 2021 exemplifies this trend by evaluating the efficacy of machine learning and big data analytics in predicting PPD. Utilizing the Arksey and O'Malley framework, this research synthesized findings from the past 12 years, focusing on various ML models, data types, and study outcomes related to PPD. The review identified 14 studies, which are listed in the references section. They predominantly used supervised learning techniques such as support vector machines, random forests, Naive Bayes, regression, artificial neural networks, decision trees, and XGBoost. Significant variability was noted in the performance of these algorithms, highlighting the need for ongoing research to refine these tools and enhance their precision and adaptability.

Our project, rooted deeply in the application of AI for mental health, targets explicitly PPD due to the limited volume of dedicated research within this area. By focusing on this underexplored domain, our project aims to enhance the predictive accuracy and clinical utility of AI tools in maternal mental health, contributing to filling the research gap and ensuring that interventions are timely and tailored to individual needs. Through rigorous analysis and development of AI and ML models, we work to establish robust, evidence-based approaches that integrate seamlessly with traditional clinical practices, thus improving the quality of care for mothers experiencing PPD. This initiative not only seeks to advance scientific understanding but also to forge practical solutions that can significantly improve early detection and intervention in PPD. This project will achieve its goals through interdisciplinary collaboration, utilizing expertise from multiple fields to develop innovative and effective solutions in this field.

Key Contributions and Implications

Collaboration among experts in various fields is vital in many areas, including technology, health, science, and ethics experts. Addressing mental health holistically benefits from the combined expertise of these professionals, especially in developing and implementing AI-powered tools for early prediction, diagnosis, and treatment. For instance, the treatment of PPD requires joint efforts from various experts. Obstetricians and gynecologists contribute crucial health data for developing predictive models for early PPD detection. Psychiatrists and psychologists provide insights into effective treatments, aiding the creation of personalized treatment systems. Social workers help compile databases of community resources, making them easily accessible through digital platforms.

We initiated research highlighting the importance of the aforementioned interdisciplinary collaboration in higher education to drive the development and application of AI in mental health care. Integrating diverse expertise enables higher education institutions to lead the way in creating innovative AI-powered solutions for mental health. This collaborative approach enhances the accessibility and effectiveness of mental health care interventions, promoting comprehensive treatment strategies and efficient resource sharing, yielding affordable and accessible solutions for many people.

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AI TASK FORCE INITIATIVE AT NORTH AMERICAN UNIVERSITY: PIONEERING A.I.-DRIVEN TRANSFORMATION IN EDUCATION, RESEARCH, AND ADMINISTRATION

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Abstract: *North American University (NAU), a small non-profit institution, recognizes the need to integrate artificial intelligence (AI) into education, research, and administration despite limited resources. To address these challenges, NAU established an AI Task Force to develop a structured approach to AI adoption. Through AI-driven management, the initiative focuses on curriculum integration, research promotion, stakeholder engagement, and operational efficiency. Additionally, NAU aims to enhance career development by fostering AI-related job readiness. By prioritizing ethical AI governance and scalable solutions, NAU seeks to position itself as a leader among smaller universities in AI adoption, ensuring long-term sustainability in an evolving technological landscape.*

Introduction

Education, including higher education, is among the most promising yet opaque areas of AI technology application. This creates new opportunities and challenges for universities. To remain relevant, educational establishments are now expected to incorporate artificial intelligence (AI) within their academic, research, and administrative functions. On the other hand, developing institutions struggle to harness AI efficiently since they do not have sufficient means and technical know-how (Kaplan & Haenlein, 2020). North American University (NAU) is a small non-profit organization that has identified this problem, and it has set up an AI task force to enable this urge on how to achieve it. While NAU aims to learn from AI initiatives at larger institutions like MIT, Stanford, and Harvard, it is focused on developing an AI framework suited to its resource-constrained environment (Vinuesa et al., 2020). The present paper outlines NAU's strategic and operational objectives concerning creating a full-fledged AI ecosystem with an emphasis on forming curricula, conducting research, and ensuring ethical governance.

Problem Statement

The changing nature of work, owing to the development of AI, means that universities ought to restructure their students' curriculum to fit into the AI job revolution, make inventions with AI's help, and use AI for administrative work. However, NAU faces the challenges of a small size institution, such as limited finances and a lack of specialists to run large, complicated AI projects. In addition, worries about such aspects of AI as privacy, discrimination, fairness and integrity of algorithms, and explainability make the task quite intricate. NAU's AI Task Force focused on solving these problems by defining a systematic approach for embedding and integrating AI into education, research, and administration, emphasizing ethical aspects and durability considerations.

The NAU AI Task Force has set realistic, prioritized goals to ensure AI integration across multiple university domains. These goals include:

1. <u>Curriculum Development and Integration:</u> The emphasis revolves around the sectional upgrading of existing subjects in the undergraduate and postgraduate curricula through the integration of artificial intelligence and

the development of new subjects that focus on artificial intelligence and its application to education, computer science, business, and criminal justice.

2. Research and Innovation: NAU will seek small, less competitive research funding opportunities to promote an AI research culture. This approach is believed to be effective. It will foster interdisciplinary collaboration by conducting AI workshops and hackathons and forming student organizations based on AI. If an environment that harbors research directed toward making developments and fostering competitive activities is created, this will not only engage students in the actual development of AI but also equip them with skills essential in the era of AI.

3. Engagement and Stakeholder Involvement: Building an inclusive community involves fully exploiting the engagement of both faculty and students. The institution anticipates that there will be interdisciplinary panels where the faculty from different departments, from literature to social sciences and engineering, will examine AI and its applicability. The task force will also engage practitioners and invite them to express present-day possibilities of interaction with the technology of intelligent systems. This synergy will support a university's understanding of the opportunities available with AI while promoting creativity and creating sustainable systems.

4. NAU will also set up an AI Resource Center to assist the staff and students with AI studies. This central location will provide AI working tools, datasets, literature, and research material for staff and students. The center will also serve as an archival center for in-house facilities aimed at AI teaching to ensure the institution is proactive in developing AI and upholding ethical standards.

5. Operational Efficiency and AI in Management of Institutional Structures: Artificial Intelligence is expected to be used in classrooms and in NAU's administration to be more effective. Under the 'AI Campus' initiative, the task force will look for AI-based alternatives to improve operations, such as streamlined processes for student services, faculty management, and data-driven decision-making. With AI automation, NAU intends to cut down on

operations where costs are incurred and improve services within the institution's limited resources. NAU management will explore the possibility of allocating specific resources to hiring people who will only be responsible for converting information to digital technology and using AI.

6. Career Development and Enhancement of Students for Adaptation into AI and Modern Workforce: The third threat is how universities, in general, and NAU, in particular, are positioning their students for the AI industry. The NAU intends to conduct such events on the AI-related job opportunities timeline and propose a structure for the AI-focused career days for the students. Students will likely get internships and mentorship from businesses involved in AI development, which will prepare them for the changing workforce and equip them with AI skills.

Conclusion

The AI Task Force of North American University provides a practical and manageable framework for introducing AI tools in the university's educational, research, and administrative processes. Instead of trying to replicate the broad programs of their mammoth counterparts, NAU's task force targets scalable and cross-disciplinary approaches within the institute's limits. Emphasizing ethical leadership, encouraging cross-disciplinary efforts, and providing platforms for education and research, NAU intends to be at the forefront of technological advances in artificial intelligence among small universities. Of course, there have been some resistances with finances and a lack of technical resources; nevertheless, with the plan and intention that NAU has regarding the integration of artificial intelligence, there is a way in which even the smaller institutions can survive in the foreseeable future which seems to be an AI era.

References

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