Generative AI Learning Environment for Non-Computer Science Engineering Students: Coding Versus Generative AI Prompting

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Abstract: This paper addresses the need for a positive and effective learning environment for engineering students in non-computer science fields to grasp Generative AI principles while navigating the intricate balance between its application and developmental insights. Drawing from pedagogical theories and cognitive science, especially Leinenbach and Corey (2004)'s Universal Design for Learning, this study proposes a framework tailored to the unique needs and backgrounds of engineering students. The framework emphasizes active learning strategies, collaborative problem-solving, and real-world applications to engage learners in meaningful experiences with Generative AI concepts. The central learning context is a M.Sc. program in management engineering with a course/training opportunity in Machine Learning Fundamentals using Python based on Google Collab. The introduction of Generative AI is based on selected Google libraries for Python. Furthermore, this paper explores various instructional approaches and tools to scaffold students' understanding of Generative AI, including hands-on projects, case studies, and interactive simulations. It also addresses ethical considerations and societal implications associated with Generative AI deployment, encouraging students to critically reflect on the broader impacts of their technical decisions. Through a synthesis of pedagogical best practices and AI development principles, this paper contributes to the ongoing discourse on effective AI education for non-computer science disciplines. By embracing a holistic approach that integrates theory with practical application, educators can empower engineering students to harness the transformative potential of Generative AI while navigating its complexities responsibly and ethically.

Keywords: Engineering education, Generative AI, Machine learning, Industrial engineering, Production engineering, Operations management

1. Introduction

The rise of artificial intelligence (AI) has fundamentally changed the game in various fields of engineering, going way beyond the usual boundaries of computer science (Brock & Von Wangenheim, 2019). As AI becomes more and more common, it's becoming increasingly important for engineering students in non-computer science disciplines to grasp AI concepts, especially Generative AI. These students need to navigate the complexities of AI development and application, which calls for a learning environment that supports both theoretical understanding, hands-on practice, and conversion to real-life settings (Yang, et al., 2020).

Generative AI, which is a branch of AI that focuses on creating new content like images, text, calculations, and music, has huge potential in a broad range of engineering fields (Radford, et al., 2019). But the ins and outs of developing and applying Generative AI models can be quite challenging, especially for students without a computer science background. That's why it's crucial to design educational frameworks that cater to their specific needs and make the most of their existing expertise (Wang & Shepherd, 2020).

This paper draws from pedagogical theories and cognitive science, particularly Leinenbach and Corey's (2004) Universal Design for Learning (UDL). UDL promotes flexible learning environments that accommodate the needs of diverse learners, engaging them through various ways of presenting information, taking action, expressing themselves, and getting involved (Meyer, et al., 2014). This approach is essential for creating a positive and effective learning environment for engineering students outside of computer science.

The main focus of this study is an MSc program in management engineering, which includes a course on Machine Learning Fundamentals using Python. To code and implement projects, students primarily use Google Colab, a user-friendly platform that allows them to experiment with Generative AI (Bisong, 2019). The introduction to Generative AI is facilitated through selected Google libraries for Python, enabling students to work with advanced AI tools and techniques without needing extensive prior knowledge of computer science (Chollet, 2021).

To help students grasp Generative AI concepts, this paper explores different teaching approaches and tools, including hands-on projects, case studies, and interactive simulations. These methods are designed to support learning step by step, giving students the opportunity to gradually build their knowledge and apply their skills in real-world situations (Chan & Lee, 2023). Additionally, the paper addresses the ethical considerations and societal impacts associated with Generative AI, encouraging students to critically think about the broader effects of their technical decisions (Floridi, et al., 2021).

By combining best practices in teaching and principles of AI development, this paper aims to contribute to the discussion on effective AI education for non-computer science disciplines. By taking a holistic approach that integrates theory with practical application, educators can empower engineering students to harness the transformative power of Generative AI while responsibly and ethically navigating its complexities (Domingos, 2015).

2. Pedagogical Framework

The Universal Design for Learning (UDL) framework, developed by CAST (Center for Applied Special Technology), provides inclusive educational environments that work for all kinds of learners (Meyer, et al., 2014). It's based on three main principles (Figure 1) that address the different needs, preferences, and backgrounds of learners: Multiple Ways of Representing Information, Multiple Ways of Acting and Expressing Knowledge, and Multiple Ways of Engaging.

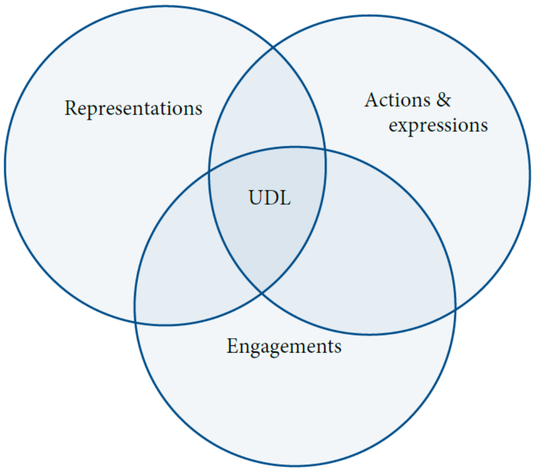

Figure 1: Pedagogical framework

Multiple Ways of Representing Information

This principle is all about giving learners different options for getting information and learning new things. Since people understand and process information in different ways, offering multiple ways of representing content makes sure that everyone can access it. Philippe et al (2020) found that using a variety of learning modes, like visual and auditory aids, can really improve understanding and retention, especially in STEM subjects (Philippe, et al., 2020).

Multiple Means of Action and Expression

This principle is all about giving learners different options to demonstrate their knowledge. We understand that everyone has their own way of expressing themselves, so it's important to offer a variety of ways to take action and show what they've learned. This includes (Novak, 2022): writing, speaking and hands-on activities such as projects, experiments, and activities that let learners apply their knowledge in real-life situations. A study by Tobin and Behling (2018) found that when students have different ways to take action and show what they know, their performance and engagement in higher education improve (Tobin & Behling, 2018). Brown and Knight (2022) also talked about how important it is to have diverse assessment strategies to encourage critical thinking and creativity in engineering students (Brown & Knight, 2022).

Multiple Means of Engagement

This principle aims to tap into learners' interests, challenge them appropriately, and motivate them to learn. Engagement can be achieved through (Meyer, et al., 2014) choice and autonomy, collaborative Learning and relevance and authenticity. Johansen et al. (2023) investigated the impact of choice and autonomy on student motivation and found significant improvements in engagement and learning outcomes (Johansen, et al., 2023). Additionally, Wiggins and McTighe (2019) highlighted the role of authentic learning experiences in enhancing student motivation and retention in STEM education (Wiggins & McTighe, 2019).

Application in Non-Computer Science Engineering Education

Multiple Means of Representation:

- To explain engineering concepts, use visualizations like neural network flow, 3D models, and simulations.
- When it comes to theoretical concepts, incorporate video lectures and podcasts.
- And for those who like to dig deeper, provide textual explanations and digital resources.

Multiple Means of Action and Expression:

- Let students show what they've learned through projects, lab work, and practical applications.
- Encourage them to present their ideas orally and have group discussions about engineering topics.
- Assess their understanding of engineering principles through written reports and design documentation.

Multiple Means of Engagement:

- Give students project choices that align with their interests and career goals.
- Foster collaboration on projects that simulate real-world engineering.
- Connect engineering problems to real-world applications, highlighting the importance and impact of the work.
- Implementing UDL in engineering education brings several benefits, including:
- Increased Accessibility: UDL ensures that all students, including those with disabilities, can access and engage with the material by providing multiple learning options.
- Enhanced Engagement: By using different teaching methods and learning activities, students stay motivated and interested.
- Improved Learning Outcomes: When education is tailored to meet the diverse needs of students, they develop a deeper understanding and retain knowledge better.

The UDL framework is essential for creating an inclusive and effective learning environment for engineering students. It's all about incorporating multiple means of representation, action and expression, and engagement. By doing so, educators can address the diverse needs of students and foster a more accessible, engaging, and successful learning experience.

3. Instrumental Approaches and Tools

Teaching Generative AI to non-software engineering students requires a multifaceted approach that includes:

- Hands-on projects
- Case studies
- Interactive simulations

Additionally, it is essential to incorporate ethical considerations and societal implications into the curriculum to prepare students for the broader impact of their technical decisions.

3.1 Hands-On Projects

Hands-on projects are an effective way to teach complex subjects like Generative AI. They allow students to apply theoretical knowledge to practical problems, enhancing their understanding and retention of the material (Kulesza, et al., 2015) , (Seo, et al., 2021).

- Step-by-Step Guidance: Providing detailed instructions for initial projects can help students build confidence. As their skills develop, they can take on more complex projects with less guidance (Chollet, 2021).
- Real-World Relevance: Projects should be designed to solve real-world problems relevant to the students' field of study. This relevance can increase motivation and demonstrate the practical utility of Generative AI (Wang & Shepherd, 2020).

Incremental Complexity: Starting with simple projects and gradually increasing the complexity can help students build their skills and avoid feeling overwhelmed (Prince, 2013).

Active Learning and Retention of Information

Studies have found that students who engage in active learning through hands-on projects retain information better and understand complex concepts more deeply compared to traditional lecture-based learning (Karpicke, 2011). Prince (2011) highlighted that active learning strategies significantly improve students' grasp of complex subjects. This includes hands-on projects. These methods enable students to apply concepts in real world scenarios.

Development of Essential Skills

Hands-on projects include problem-solving critical thinking and collaboration in the field of Generative AI (Kolodner, et al., 2011). Matar et al. (2024) discussed the integration of project-based learning in AI education. They achieve this while simultaneously building essential skills. Their findings suggest that students who engage in PBL are better prepared for the complexities of the AI field (Matar, et al., 2024). It demands critical evaluation of algorithms and their outputs. Collaborative efforts integrate AI solutions across various domains (Floridi, et al., 2021).

For instance, a project involving development of a Generative Adversarial Network (GAN) for creating synthetic images would require students to:

- -Solve technical problems related to model training. Optimize the model (problem-solving skills).
- -Critically evaluate the quality. Analyze ethical implications of generated images (critical thinking skills).
- Collaborate with peers. Integrate diverse expertise and perspectives (collaboration skills).

Students can work on projects that involve building generative models using frameworks like TensorFlow or PyTorch. For instance, creating Generative Adversarial Network (GAN) to generate images. Alternatively, they might build a variational autoencoder (VAE) for data compression. This presents practical challenges of working with large datasets (Chollet, 2021). Goodfellow et al. (2014) introduced GANs. Building models significantly enhances students' understanding of neural networks and deep learning principles (Chollet, 2021), (Goodfellow, et al., 2014).

3.2 Case Studies

The learning ladder of generative AI for management engineering students is proposed in Figure 2. To illustrate the learning ladder of generative AI for management engineering students, let's delve deeper into each stage of the process and this will help provide a comprehensive understanding of how each step builds on the previous one, forming a coherent path for integrating generative AI into business solutions.

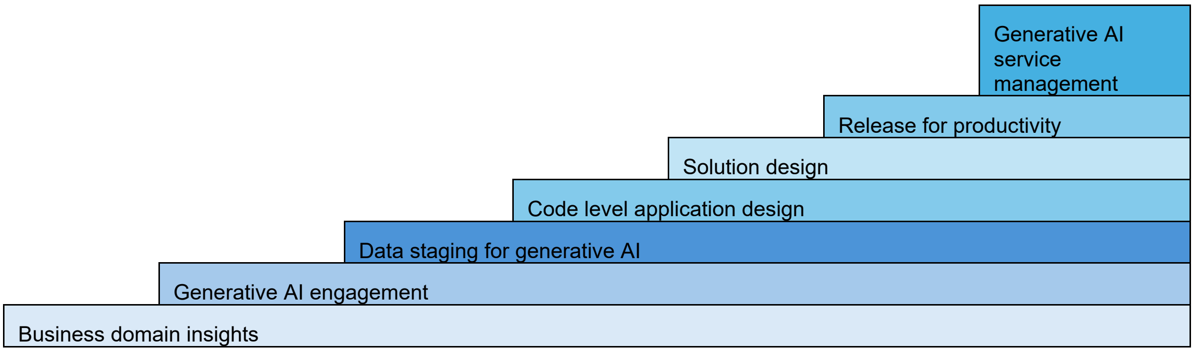

Figure 2: Learning ladder of Generative AI for management engineering students

Business Domain Insights: Understanding the business domain is crucial as it provides the context in which AI solutions will operate. This stage involves identifying business challenges and opportunities, setting objectives and understanding the nuances of industry (Sun, et al., 2018). Davenport and Ronanki (2018) explores how businesses are leveraging AI technologies to gain insights and improve decision-making processes.

Generative AI engagement: Engaging with generative AI involves selecting appropriate AI models, fine-tune them and understanding their capabilities. This stage sets the foundation for how AI can be utilized to address business needs (Brown, et al., 2020). Huang and Rust (2021) examines the impact of AI on service industries, with a focus on how AI technologies, including Generative AI, are used for market analysis and understanding customer needs (Huang & Rust, 2021).

Data staging for generative AI: Data staging involves preparing and preprocessing data to ensure it is suitable for AI model training and evaluation. It includes data cleaning, normalization and augmentation and splitting data into training and test sets.

Code level application design: This phase involves designing the application codebase including the architecture, APIs and integration with generative AI models. The focus is on modularity, scalability and maintainability.

Solution design: Solution design involves integrating AI models into full-fledged solution that meets business requirements. This includes designing the user interface, backend services, data pipelines, and deployment strategy.

Release for productivity: Releasing the solution involves deploying the application into production environment. This ensures it is reliable and scalable. It also must be maintainable. Continuous integration and continuous deployment (CI/CD) practices are critical here.

Generative AI service management: Service management is the process of monitoring and maintaining the deployed AI solution to ensure it still meets business needs. It involves: Performance monitoring, updating models, and handling user feedback.

Libraries

Google Colab is a cloud-based Jypyter notework environment and it supports Python and various popular libraries. It provides free access to GPUs and Tensor Processing Units (TPUs). TPUs are application-specific integrated circuits developed by Google specifically for accelerating machine learning workloads. They are designed to handle tensor operations. These operations are core part of the computations in machine learning models. This is particularly true for those involving deep learning. See Table 1.

Table 1: Key (generative) libraries in Google Colab

Libraries	Installation	Usage
TensorFlow and Keras	'!pip install tensorflow'	TensorFlow and Keras provide a robust framework for building and training neural networks, including generative models.
PyTorch	'!pip install torch torchvision'	PyTorch is another powerful library for deep learning, favored for its dynamic computation graph.
Hugging Face Transformers	'!pip install transformers'	Ideal for natural language processing tasks with pre-trained models like GPT-4.
Open AI API	'!pip install openai'	Access OpenAI's powerful models such as GPT-4 for text generation.
DALL-E-Mini	'!pip install dalle-mini'	Generate images from textual descriptions using DALL-E.
RunwayML	Varies based on the model; can be accessed via API or web interface.	Provides various generative models with a user-friendly interface

There are also other platforms which can provide the necessary computational resources, pre-built environments and integration with AI libraries to   development and deployment of Generative AI models: Google Cloud AI Platform (Rajpurkar, et al., 2020), IBM Watson Studio, Paperspace Gradient, Run, Colab Pro+ etc.

3.3 Interactive Simulations

Students use insight in the industrial engineering field to capture the business problem. This gives the students ability to understand critical data, collect this with the appropriate context, and do the staging of data.

The generativity ensures that data a properly parsed. Algorithmically students can get insights from a statistical perspective with a minimal effort. This process can be elevated into an operating procedure in the production to secure precision, quality, reduce variability, and validate machining parameters. The students embeddedness in the production organization makes it accomplishable to implement the procedure for statistical process control and tooling. Here is an example of production line for wood furniture components with a simplified production line in Figure 3 and the data collection approach illustrated in Figure 4.

Figure 3:Simplified production line for wood analysis and cutting

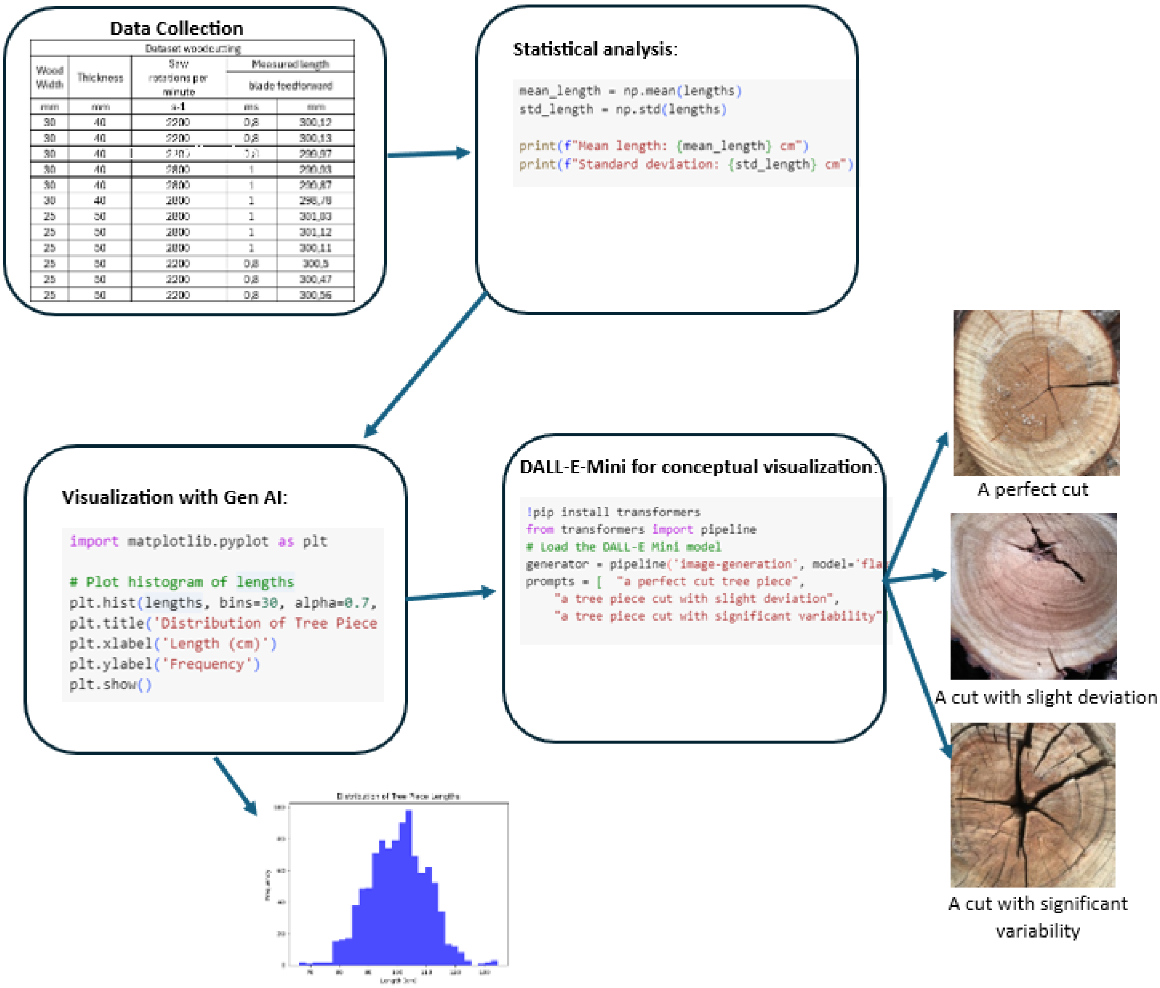

Figure 4: Generative thinking for digitalisation of wood end quality analysis

Analyzing the variability of cutting tree pieces with an automatic saw using generative AI thinking with a model like DALL-E-Mini involves a few conceptual steps. While DALL-E-Mini is designed for generating images from text prompts, the principles behind generative AI can help us think about how to analyze and visualize variability in a manufacturing process. Here's a conceptual approach.

- **Data Collection**: Gather data on the dimensions of the tree pieces cut by the automatic saw. This data should include measurements like length, width, thickness, and any other relevant parameters.

- **Statistical Analysis**: Use statistical methods to analyze the variability in the data. This could involve calculating the mean, standard deviation, and other measures of spread for each parameter.
- **Visualization**: Generate visual representations of the data to better understand variability. This is where generative AI can provide interesting insights by creating visual simulations or representations of the data distribution.

Implementation

- **Data Collection**: We generate a synthetic dataset of tree piece lengths using a normal distribution to simulate real-world variability.
- **Statistical Analysis**: Calculate mean and standard deviation to understand the central tendency and spread of the data.
- **Visualization with Generative AI Principles**: Use histograms to visualize the distribution of lengths. In a generative AI context, this step could involve creating synthetic images that represent the statistical properties of the dataset.
- **Using DALL-E-Mini**: Generate conceptual images based on text prompts that describe different cutting scenarios. These images can help visualize the variability qualitatively.

This approach combines traditional statistical analysis with the creative capabilities of generative AI to provide both quantitative and qualitative insights into the variability of tree piece cutting.

4. Framework

In management engineering, understanding the basics of machine learning (ML) is essential for applying generative AI in industrial contexts. Students without a software engineering background need to grasp core ML concepts, generative AI techniques, data preparation, model training, and evaluation. These foundational skills are vital for addressing industry-specific challenges and opportunities. To provide more specific context, specific generative AI methods, such as Generative Adversarial Networks **(**GANs**)** for creating realistic images and Variational Autoencoders **(**VAEs**)** for data compression and reconstruction, could be briefly mentioned. These methods are widely used in applications like synthetic data generation for testing business models or design optimization in manufacturing. Moreover, students will learn to manage generative AI services, focusing on ethical considerations and stakeholder engagement.

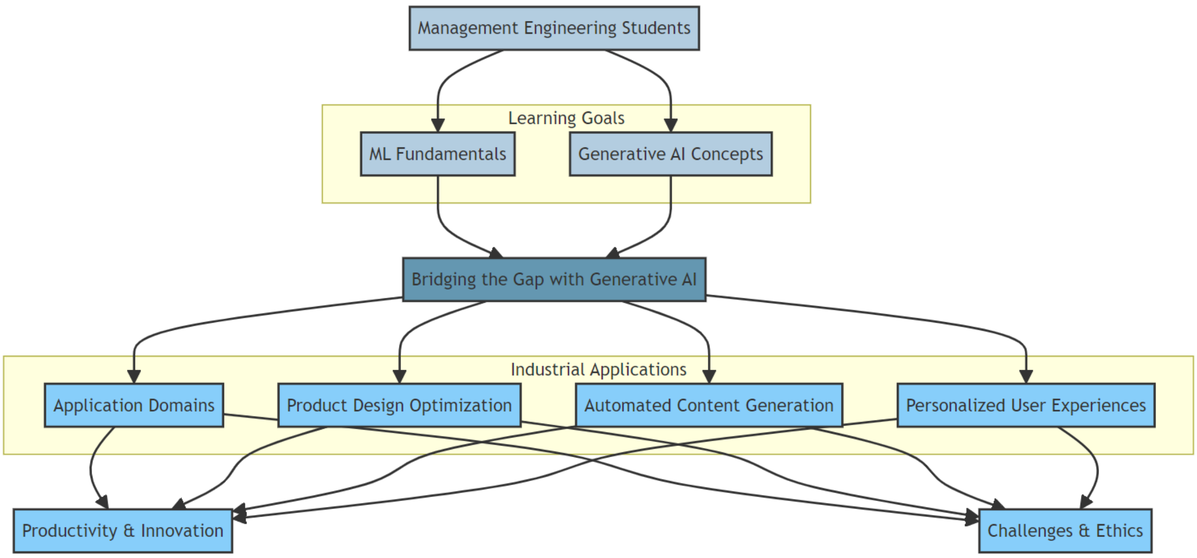

Figure 5: Framework of teaching generative AI for production engineers

Bridging the Gap: The connections between the education's learning goals and the industrial application steps using generative AI are shown here. For example, mathematical foundations lead to understanding business domain insights, algorithm understanding leads to generative AI engagement, and so on. Generative AI plays a pivotal role in bridging the gap between machine learning education and industrial applications. By integrating generative AI concepts and technologies into the curriculum, students gain practical experience that prepares them for real-world challenges. The scientific references provided illustrate how generative AI is being utilized across various domains to drive innovation, enhance productivity, and manage AI services effectively. This holistic approach ensures that the theoretical knowledge gained in the classroom is directly applicable to solving practical business problems, thus closing the gap between academia and industry.

Generative AI techniques have revolutionized various industries by tackling complex problems such as automated content generation, product design optimization, and personalized user experiences. Generative AI optimizes product design processes by generating and evaluating design alternatives based on specified constraints and objectives. Bendoly et al. (2023) explores the integration of generative design techniques with additive manufacturing processes. It showcases how AI-driven generative design tools enable iterative optimization of product designs, leading to enhanced performance, reduced material waste, and accelerated innovation cycles (Bendoly, et al., 2023). Furthermore, Generative AI automates the creation of textual, visual, or multimedia content, enhancing efficiency and creativity in marketing, journalism, and entertainment. Benites et al. (2023) discusses advancements in automated text generation techniques using generative models like GPT (Generative Pre-trained Transformer) and their applications in content creation across various domains, highlighting improvements in natural language understanding and generation capabilities (Benites, et al., 2023). Jain and Singhal (2022) suggest surveys advanced recommendation systems powered by generative AI algorithms. They further discuss leveraging user data to generate personalized recommendations in e-commerce, streaming platforms, and digital marketing (Jain & Singhal, 2022).

5. Impact on Productivity and Innovation Vs Challenges and Ethical Considerations

Generative AI, especially in industrial contexts, shows immense promise in boosting productivity by automating intricate tasks and coming up with innovative solutions. For example, with Generative Adversarial Networks (GANs) used for synthetic sales data generation, businesses can now mimic various market conditions and customer behaviors without needing extensive real-world data collection. This means they can test business strategies and product offerings more quickly and iteratively, leading to a faster time-to-market and more informed decision-making (Karras, et al., 2019). For management engineering students, grasping and applying these AI-driven efficiencies can be transformative for business simulations, predictive analytics, and strategy development.

Generative AI is revolutionizing product design and development by enabling engineers and designers to explore a multitude of design possibilities beyond what humans could traditionally conceive. Tools like DALL-E and Stable Diffusion facilitate the creation of unique, high-quality visuals that can inspire new product concepts and marketing strategies (Ramesh, et al., 2021).

Generative AI excels at analyzing vast amounts of user data to create tailored content and recommendations, thereby enhancing personalized user experiences (Covington, et al., 2016). Moreover, AI-generated content, such as personalized emails, advertisements, and product suggestions, can significantly enhance customer engagement and drive sales.

Learning to apply AI in personalizing user experiences can help students develop customer-centric business models and strategies, ultimately improving business outcomes.

Challenges and Ethical Considerations

One of the foremost challenges in deploying generative AI is ensuring data privacy and security. These AI systems often require vast amounts of personal and sensitive information. Therefore, it's crucial to handle this data responsibly, anonymize it properly, and protect it from breaches. The General Data Protection Regulation (GDPR) and similar privacy laws impose strict requirements on data handling practices (Voigt & von dem Bussche, 2017). Management engineering students must be educated on the importance of data privacy and security.

Generative AI models can unintentionally perpetuate or amplify existing biases in their training data. For instance, if a GAN used in hiring processes is trained on biased data, it might produce biased hiring recommendations (Buolamwini & Gebru, 2018). Addressing these biases requires thorough auditing of training data and implementing fairness constraints in AI models. Students need to grasp the ethical implications of AI and learn techniques to identify and mitigate biases in AI systems, ensuring fairness and equity in AI-driven decisions. Another critical consideration is the ethical use of AI-generated content. AI can create highly realistic fake images, videos, and news, which can be misused to spread misinformation or manipulate public opinion (Chesney & Citron, 2019). Management engineering students should be trained to develop and adhere to ethical guidelines when using AI-generated content, promoting the responsible use of AI technologies. Ethical challenges, such as algorithmic bias, data privacy concerns, and the broader societal impacts of AI, should also be emphasized as they are critical for stakeholder trust and engagement. For instance, bias in AI models can result in unfair treatment in areas like recruitment, while privacy issues can lead to misuse of sensitive data. Addressing these concerns requires interdisciplinary collaboration between engineers, ethicists, and policymakers to ensure that ethical challenges are tackled comprehensively.

The automation of tasks through generative AI can lead to job displacement, especially in roles involving routine and repetitive tasks. While AI can create new job opportunities and enhance productivity, it also requires a workforce skilled in AI and data science (Brynjolfsson & McAfee, 2014). Investing in education and training programs to reskill workers and prepare them for the AI-driven job market is crucial to mitigating the negative impact on employment. For students, this highlights the importance of continuous learning and skill development in AI and related fields to remain relevant in the evolving job market.

6. Conclusion

Generative AI offers significant potential for boosting productivity and fostering innovation across various industries. However, it also presents substantial challenges and ethical considerations that must be addressed. Generative AI's deployment in industries like healthcare (e.g., AI-assisted drug discovery) and manufacturing (e.g., generative design for optimized production) offers concrete examples where both its benefits and ethical concerns are at play. These examples illustrate how AI can boost productivity while also raising complex ethical dilemmas. The students can begin addressing these challenges through interdisciplinary learning, collaborating with stakeholders from diverse fields to ensure they are well-equipped to handle the ethical, technical, and societal implications of AI in their future careers. For management engineering students, learning to balance the benefits of AI with responsible and ethical practices is essential to ensure that AI deployment positively contributes to society. Future research and development should focus on enhancing the fairness, transparency, and accountability of AI systems while promoting inclusive and sustainable growth.

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