Chapter 2
Unleashing the Potential:
Positive Impacts of Generative AI on Learning and Teaching

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ABSTRACT

Generative artificial intelligence, anchored by large language models (LLMs), is significantly altering the educational landscape. This chapter examines the impact of generative AI on education, illustrating its capability to create personalized content and transform learning environments. Despite concerns over academic dishonesty facilitated by LLMs, the chapter argues against a regressive stance and advocates for the constructive integration of AI into educational practices. By drawing on theories of learning, the chapter elucidates the pedagogical implications of generative AI and describes specific use cases in language learning, computer science, and mathematics. Highlighting both the potential and limitations of this emerging technology, the chapter posits that generative AI is not merely a disruptive force, but a revolutionary tool poised to redefine the methodologies of teaching and learning.

1. INTRODUCTION

As the frontier of artificial intelligence (AI) continues to expand, one of its subfields, generative AI, is reshaping the educational landscape by producing engaging, personalized content and transforming learning environments. Large Language Models (LLMs) that underpin generative AI employ pattern matching to generate human-like text (Tang, Chuang, & Hu, 2023) represent the latest disruptive technology impacting society (Utterback, & Acee, 2005). In the past, many educators primarily relied on essays or extended answers from students to demonstrate content mastery (Farthing, Jones, & McPhee, 1998). However, with the advent of LLMs such as ChatGPT, less scrupulous students can simply input the question as a prompt and receive a grammatically perfect and coherent answer, albeit one that may contain factual errors (Malinka et al., 2023). Reactions of educational institutions to generative AI vary

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greatly: some have banned it, some have embraced it, while others remain undecided and leave the choice up to individual faculty (Kasneci, 2023). Previous disruptive technologies, such as calculators in mathematics, electronic dictionaries and machine translation in language learning, the internet across all subjects, are now widely accepted by educators. Considering the remarkable power of generative AI, adopting a luddite-like stance seems futile. Thus, this chapter argues in favor of embracing AI and empowering teachers and learners to utilize it effectively.

This chapter investigates the profound effects of generative AI on learning and teaching. Education is underpinned by theories of learning, which are described in relation to the pedagogic use of generative AI. Learning with AI and the creation of educational materials by AI are next addressed. Specific use cases related to language learning, computer science and mathematics education are described and discussed. Potential educational applications are then suggested. This chapter aims to provide a comprehensive understanding of the benefits of generative AI in educational settings while acknowledging its limitations. AI appears set to unleash a sea change in both the way that students learn and the way that teachers teach. Education, like most areas tends to improve incrementally, but we are now experiencing a radical innovation, which could be the harbinger of a new mode of education.

2. THEORIES OF LEARNING RELATING TO GENERATIVE AI

Teachers tend to draw eclectically from a range of techniques and strategies, often without explicitly adhering to a single underpinning theory (Moreira dos Santos, 2020). Individual teachers cultivate their own teaching philosophies, shaped by experience, context, and the unique needs of their students. These philosophies may be formally codified into a teaching philosophy statement or may be more nebulous and simply exist in the mind of the educator (Fitzmaurice & Coughlan, 2007). However, it is useful to understand the four main learning theories that have historically informed educational practices: behaviorism, cognitivism, constructivism and social constructivism (Adams, 2006; Bredo, 1997; Tomic, 1993).

2.1 Behaviourism and Cognitivism

Behaviorism was the dominant learning theory in the early to mid-20th century. Grounded in the work of psychologists like John B. Watson (Watson, 2017) and later B.F. Skinner (Todd, & Morris, 1995), behaviorism focuses on observable behaviors and the stimulus-response model where positive reinforcement leads to learning (Fisher, Piazza, & Roane, 2021). Cognitivism developed as a response to the limitations of behaviorism, shifting the focus from observable behaviors to the internal processes of the mind (Amsel, 1989). This learning theory postulates that understanding how information is received, processed, stored, and retrieved by the brain is essential for effective learning. Cognitivism provides a framework for examining how learners make sense of complex information, solve problems, and transfer knowledge, emphasizing the role of mental constructs like memory, perception, and attention in the learning process. Despite their differing perspectives on the nature of learning, behaviorism and cognitivism share some similarities, particularly in their systematic approaches to understanding learning processes. Both theories aim to develop structured methodologies for education, striving for predictability and control in learning outcomes. They both rely on empirical evidence and experimentation to validate their principles, leaning on the scientific method for credibility. Additionally, each theory places importance on the role of the environment in shaping either behavior or cognitive structures. Behaviorism emphasizes external stimuli and reinforcements as key environmental factors, while cognitivism focuses on how information from the environment is processed and organized in the mind. Thus, while behaviorism and cognitivism may differ in what they consider the primary locus of learning—external behaviors or internal mental processes—they both acknowledge the interplay between the individual and the environment in the learning process.

While behaviorism and cognitivism offer valuable insights into the mechanics of learning, either through observable behaviors or mental processes, they do not fully encapsulate the complexities of how individuals construct knowledge in a social context. This brings us to constructivism, a theory that attempts to bridge the gap by emphasizing the learner's active role in building understanding and making sense of information. Unlike behaviorism and cognitivism, constructivism places a greater focus on the ways learners interpret, filter, and transform incoming information based on their previous experiences and social interactions (Bada & Olusegun, 2015). It challenges the notion of the teacher as a mere dispenser of knowledge, advocating instead for a more collaborative and interactive educational environment.

2.2 Constructivism and Social Constructivism

Constructivism holds that learners actively construct their own understanding and knowledge of the world through hands-on experiences and reflection (Nagowah & Nagowah, 2009). This theory, often attributed to educational psychologists like Jean Piaget (Ojose, 2008) and Jerome Bruner (Rannikmäe, Holbrook, & Soobard, 2020), shifts the focus away from teachers transmitting information to learners passively receiving it. Instead, constructivism emphasizes problem-solving, critical thinking, and the application of knowledge in real-world contexts. It encourages learners to build new ideas upon the foundation of their existing knowledge and experiences, thus promoting a deeper understanding of the subject matter.

Social constructivism (Adams, 2006), an extension of constructivism, takes the theory a step further by emphasizing the importance of social interactions and cultural context in the learning process. Rooted in the work of Lev Vygotsky (1987), social constructivism argues that knowledge is constructed through dialogue, negotiation, and collaboration. This theory acknowledges that individual cognitive development is not an isolated process, but rather one deeply influenced by social and cultural factors. In a social constructivist classroom, social interaction is not just a byproduct of learning but a fundamental component of it. Learners work together to solve problems, debate ideas, and engage in cooperative projects, often employing tools and symbols from their cultural context to aid in the learning process.

These four theories offer frameworks that can guide educators in developing effective teaching methods, even as they adapt and blend these approaches in their own unique ways. It should be noted that these learning theories were developed in the pre-digital era, and so do not explicitly take into account the impact that computers, or more specifically, the software programs, may have on learning. In the pre-internet era, access to the World Wide Web was not readily available to educators. In its early days, the web was a content delivery network (Web 1.0). The web developed into a kind of social network (Web 2.0), a decentralized database (Web 3.0) and is currently transforming into a network in which interactions between users and AI are commonplace (Web 4.0) (Nath, 2022). With the rapid increase in reliance on technology, ubiquitous access to the internet via wifi and the widespread ownership of internet-enabled devices (Kukulska-Hulme, 2006), such as mobile phones, tablets and laptops; a fifth learning theory that takes into account this connectivity was born.

2.3 Connectivism

Proposed by George Siemens and Stephen Downes, connectivism (Downes, 2022) asserts that in an age of abundant information and rapidly evolving technologies, learning is less about acquiring static knowledge and more about the ability to navigate complex networks of information. Unlike traditional learning theories, which primarily focus on individual cognition or social interaction, connectivism extends the learning sphere to include the digital and networked environments. It suggests that learning occurs in various settings, not just in the individual or the classroom, but also through online communities, social media, and even through interaction with intelligent systems. Connectivism emphasizes the importance of understanding how to learn, fostering adaptability, and nurturing connections that help learners plug into ever-changing streams of information. In this context, the role of educators shifts towards facilitating these connections and helping learners cultivate skills to manage, evaluate, and integrate information from diverse sources.

The intersection of generative AI and educational theories opens new vistas for innovative learning experiences. Particularly, applying connectivism to generative AI presents a compelling way to restructure and enrich learning environments. Firstly, generative AI serves as a dynamic hub in a learner's personal learning network (Warlick, 2009). Acting as both a source and conduit for information, AI extends the learning ecosystem, linking learners to a myriad of educational resources and social connections. Secondly, machine learning algorithms can personalize the educational journey for each learner (Tetzlaff, Schmiedek, & Brod, 2021). This enhanced tailoring not only empowers learners but also significantly augments their personal learning environments. Thirdly, AI has the capability to process vast sets of data to deliver the most current and relevant information. This assists learners in making timely, well-informed decisions and effectively navigates them through complex and often overwhelming informational landscapes. Fourthly, AI's strength lies in its ability to understand and adapt to specific, real-world contexts. It can simulate or model intricate systems, thereby providing learners with problem-solving opportunities that mirror real-world challenges. This helps learners to develop skills that are both contextually sensitive and broadly applicable. Finally, the role of AI in social and lifelong learning cannot be underestimated. Generative AI can facilitate social interactions in digital learning environments through features like online community forums and real-time collaborative projects. This encourages continuous learning and adaptability, both of which are key aspects of a lifelong educational journey. In combining these various facets, generative AI acts as a multi-dimensional tool in modern education, aligning well with different learning theories to provide a holistic, dynamic, and deeply enriching learning experience.

2.4 Section Summary

Generative AI, particularly Language Learning Models (LLMs) like GPT-4, presents exciting new possibilities for education that intersect with multiple learning theories. From a behaviorist perspective, AI can provide immediate feedback and reinforcement, creating a responsive learning environment (Hall Lang, 2023) that can be tailored to individual progress. In a cognitivist framework, AI can assist in information processing, offering problem-solving exercises and dynamic examples that adapt to a learner's cognitive level. Constructivism and social constructivism find application in AI's ability to facilitate hands-on, problem-based learning experiences and social interactions. For instance, AI can simulate realistic collaborative tasks or discussions, enabling learners to construct knowledge actively in a social context. Lastly, in a connectivist view, AI serves as a node in a learner's network, providing access to a vast, interconnected web of information, and helping learners adapt to the rapidly changing landscape of knowledge and technology. Thus, generative AI can be a multifaceted tool in education, complementing and enhancing various learning theories to provide a more adaptive, personalized, and comprehensive learning experience.

3. LEARNING WITH GENERATIVE AI

In this section, I argue that LLMs, such as ChatGPT, can function as both tools and (to some extent) as tutors (Ausat et al., 2023). However, it should be noted that their primary role is as a tool, given their out-of-the-box default is as a tool rather than as a teacher. To provide an analogy, LLMs share more similarities with slide rules and calculators, than teachers of mathematics. Both slide rules and calculators help learners calculate answers to complex arithmetic problems without needing to resort to long division or multiplication, but neither of the tools helps learners understand the underlying declarative knowledge and apply the procedural knowledge (Saks, Ilves, & Noppel, 2021), and neither can correct the misuse of the tool. Getting ChatGPT to provide support in a similar way to a human teacher is much more challenging, and requires both a very specific and well-defined learning context and aims, and a knowledge of sophisticated prompt engineering (Heston, & Khun, 2023) to be able to direct the LLMs.

AI chatbots can serve as valuable resources that offer supplementary support to learners. In the context of a Japanese university, where diverse learning needs and preferences are prevalent, generative AI presents an innovative solution to address these challenges. By responding to queries, offering personalized learning materials, and assessing student performance, AI chatbots augment the learning experience and tailor it to individual requirements. Lectures and large classrooms are the norm in many universities. Personalizing and tailoring materials to groups of learners is possible to a certain extent, but providing individualized learning materials is not feasible. LLMs, however, are scalable and trainable (Xue et al., 2023), and so with a clear remit and a narrow field, may be able to provide individualized learning. A case in point is the intelligent tutoring system to teach applications of fuzzy logic (Marciniak and Szczepański, 2020). The lack of real-world understanding, their (current) inability to recognize emotional states and actions of learners, severely limits their ability to act as teachers. However, their vast knowledge base and pattern-matching prowess outstrip any individual.

Generative AI can be trained to dynamically adapt to a student's learning style, pace, and academic needs, providing a level of personalization that is difficult to achieve in a traditional classroom. Its extensive knowledge base enables AI to serve as a supplementary tutor, offering insights, explanations, and resources across a wide range of subjects. However, it is important to acknowledge some shortcomings. Generative AI, while expansive in its knowledge, lacks the understanding and emotional intelligence that a human educator brings to the learning experience (Schuller & Schuller, 2018). Additionally, the effectiveness of AI as an educational tool is highly dependent on the quality of its programming and the data it's trained on (Wang et al., 2023), which can sometimes limit its applicability in more complex or academic discussions. Nonetheless, for university learners navigating the ever-expanding landscape of knowledge, generative AI promises a more adaptive, personalized, and comprehensive educational journey.

Situated learning (Mandl & Kopp, 2005) posits that learning is most effective when it occurs in the context where the knowledge or skills will be applied. Rather than just internalizing isolated facts or concepts, this theory suggests that learning involves full engagement with the practices, tools, and culture of a particular community. For example, medical training through internships or residencies does not solely rely on textbooks or lectures. Medical students engage in rounds, diagnose real patients, and work under the mentorship of experienced physicians. This kind of real-world experience helps them understand not just the technical aspects of medicine but also nuances like bedside manner, interdisciplinary collaboration, and ethical decision-making.

AI models are often trained on large, diverse datasets but are usually deployed in very specific contexts. The traditional way of training these models lacks a "situated" element, as it is not inherently contextual or pragmatic. However, the concept of situated learning can be applied to improve their performance. For instance, AI models could be fine-tuned within specific environments where they will operate, effectively making them apprentices within those domains. By doing so, the AI models could develop a more nuanced understanding of their operational environment, making them more effective and reliable. Integrating situated learning principles into generative AI training could move us away from a purely data-centric approach to a more context-aware, socially-informed model of machine learning.

Distributed cognition (Carr, Johnson, & Bush, 2017) is a theoretical framework that extends the boundaries of cognition beyond the individual mind to include interactions with other agents, artifacts, and the surrounding environment. It theorizes that cognitive processes, such as problem-solving and decision-making, are not confined to single individuals but are shared across multiple components of a system. This approach views cognition as a collaborative, socially-situated activity that integrates people, tools, and context. For example, the use of generative AI in education can be seen as a form of distributed cognition. Here, the AI model becomes an extension of both the teacher's and the students' cognitive processes, providing personalized feedback, generating quiz questions, or suggesting resources for further study. It's not just the human actors—the teachers and students—who are participating in the learning process; the AI becomes a co-participant that augments and enriches the cognitive environment. Through real-time interactions and data analysis, the AI system adapts to the students' learning styles and needs, while teachers can focus on more complex aspects of teaching that machines cannot handle. This creates a dynamic, interactive cognitive ecosystem that evolves to optimize educational outcomes.

4. GENERATING EDUCATIONAL MATERIAL USING AI

Generative AI is significantly transforming the writing process in multiple domains, Educators can harness its potential to generate personalized content for individual learners based on their abilities, interests, and learning styles (Mikhailava et al., 2022). The landscape of educational material creation is starting to undergo a profound transformation through the integration of generative AI. LLMs have the capacity to tailor educational content to the unique needs and preferences of individual learners, revolutionizing the way knowledge is disseminated. By harnessing the power of generative AI, educators are now empowered to craft personalized learning experiences that cater to the diverse abilities, interests, and learning styles of their students.

Pedagogical considerations play a pivotal role in the creation of effective educational materials. With generative AI, educators can seamlessly embed pedagogical strategies that cater to individual learning preferences. One of the most remarkable aspects of generative AI is its ability to generate educational content that is truly bespoke. For example, by analyzing a learner's proficiency level, preferences, and past interactions, AI algorithms can craft materials that align precisely with the individual's learning path (Bitsch, Senjic, & Kneip, 2022). This personalized approach goes beyond a one-size-fits-all model, allowing each learner to engage with materials that are both challenging and attainable, thereby fostering a deeper and more meaningful understanding of the subject matter.

While commonly associated with tasks like language translation and text generation, the application of generative models to language education offers a groundbreaking opportunity to explore linguistic nuances and complexity. By harnessing the capabilities of generative AI, language teachers can uncover intricate sentence patterns and foster a deeper understanding of language structures that might otherwise be overlooked in conventional coursebooks. For example, AI can produce multiple sentences that express the same meaning but with varying complexity and formality. Through carefully curated examples, teachers can highlight subtle differences in vocabulary, syntax, and grammatical structures, enabling learners to grasp the intricacies of high-level language usage.

In the field of computer science education, generative AI can craft teaching materials, tailored to the specific requirements of learners, which deal with intricate concepts, such as expert systems, machine learning and information ethics. Concepts can be presented in a manner that resonates with learners' cognitive styles, promoting a deeper understanding and retention of knowledge. The personalized nature of bespoke content enables educators to create materials that can address multiple purposes. This simplifies the process of aligning the educational materials with the aims and objectives of a course. For example, materials generated to teach expert systems were designed to convey knowledge and increase engagement through activity-based tasks. However, the AI-generated course materials that formed the basis of an information ethics course were designed to enhance engagement with the course content and simultaneously develop their ability to present logical arguments.

Although ChatGPT is designed to generate texts, there are a number of AI tools that can generate images, videos and slideshow presentations. Learners who thrive in visual contexts can be provided with AI-generated multimedia-rich content, while those who prefer textual explanations can receive in-depth written explanations. This level of personalization not only caters to diverse learning styles but also acknowledges the significance of individual cognitive processes in the learning journey. Generative AI can enhance personalized learning experiences and foster a deeper engagement with complex subject matter.

5. USE CASES

I will examine the effectiveness of such generative AI learning experiences in various courses, drawing on recent trials of the use of generative-AI conducted at a Japanese university. In this section, I discuss four use cases showing how ChatGPT can be used to enhance learning.

5.1 Use Case One: Feedback on Language Use

In the educational setting with Japanese undergraduates, one noteworthy application of generative AI focuses on enhancing English writing skills. Twenty-eight computer science majors enrolled in an English language course were tasked with writing a paragraph on a technical topic in English. The mean English language proficiency of the cohort is B1/B2 (independent learners) on the Common European Framework of Reference for Languages (CEFR). After completing their initial drafts, they leveraged generative AI to obtain various types of feedback through different prompts, which were suggested by their teacher. For example, one prompt has the AI identify grammatical errors without offering corrections, giving students a chance to self-correct and assimilate the language rules. Another prompt instructs the AI to both correct these errors and provide an itemized list explaining each correction, offering a comprehensive review, enabling learners to see how their writing may be improved and to check the reason for each improvement. This helps them not only improve their individual draft; but over time, they should be able to notice the trends in the advice given by the LLM. Additionally, to bridge potential language gaps and deepen understanding, students prompted the LLM to translate a paragraph into Japanese twice: once focusing on direct translation and once using idiomatic expressions. This opens up the possibility of better understanding the impact of sociocultural conventions, and noticing how even simple phrases in one language receive different idiomatic translations based on the context.

Several interesting observations emerged in terms of student response and utilization of the AI tool. First, many students switched to converse with ChatGPT in Japanese, not merely for ease of communication but as a tactical approach to better grasp complex ideas before translating them back into English. This enhanced their understanding and control of English language structures by translating them from their native language. Second, a form of collaborative inquiry emerged as students engage in iterative conversations with ChatGPT, not only to better understand the AI's feedback but to dig deeper into the linguistic and conceptual intricacies of their writing assignments. They would pose a question, discuss the AI's response, and then ask follow-up questions to refine their understanding. This iterative dialogue allowed the students to be active learners, encouraging them to be more analytical and critical, rather than passive recipients of linguistic advice.

Overall, generative AI served as an invaluable and versatile tool becoming an interactive co-educator in a bilingual educational environment, which can provide model texts, compare and contrast any texts in terms of content and language, and can provide feedback in multiple forms, giving learners the opportunity to receive feedback that is most relevant to their current language proficiency and learning objectives.

5.2 Use Case Two: Dynamic Language Assessment

In this second use case, the LLM provided tailormade advice at multiple levels based on revisions made to a text. In order to function as a dynamic language assessor, the LLM first needed to be trained. This was achieved with some sophisticated prompt engineering. The prompts created by a computer scientist with expertise in deep learning models were shared with students studying in a natural language processing laboratory. Six undergraduates (with B2 CEFR proficiency in English) volunteered to utilize ChatGPT-4 as a dynamic language assessment tool (Lantolf, & Poehner, 2004).

The students researched a specific domain within computer science, such as natural language processing, databases, or cybersecurity. Once they had sufficient information, they drafted a paragraph describing some highly specific aspect of their chosen area. ChatGPT was trained using carefully crafted prompts to function as a dynamic language assessment tool for this task. The training involved identifying and labelling five types of errors that occur in scientific writing, namely errors with accuracy, brevity, clarity, objectivity and formality (Blake, 2021). The next step was training the LLM to provide feedback in sequence starting with the most implicit and transitioning incrementally to more explicit feedback until the learner can correct the error. Once trained, learners submitted their paragraph to the LLM for feedback. The AI provided graduated feedback, which unfolds in a manner congruent with Vygotsky's Zone of Proximal Development (Vygotsky, 1987), aiding the learners to progress from where they currently are to where they can be with guided assistance.

Initially, the feedback started with the most implicit forms, like offering simple prompts that encourage students to reconsider sentences or phrases that might be problematic, without specifically identifying the errors. This resembles a form of Brunerian "scaffolding," (Shvarts & Bakker, 2019) wherein the support is just enough to aid the students in reaching the next level of understanding on their own. As the students iterate on their work, the AI's feedback becomes progressively more explicit. It transitions from highlighting areas that need attention to providing more direct guidance, such as suggesting alternative sentence structures or vocabulary.

Towards the end of this graduated feedback loop, the AI offers the most explicit form of feedback, including corrections with itemized explanations. This not only makes students aware of their mistakes but also educates them on the reasoning behind the correct forms. Although ChatGPT was able to provide feedback in graduated levels, in this small-scale trial its ability to grade their advice and provide feedback in increasingly more explicit ways was not comparable to a human.

In spite of its potential, the small-scale trial revealed some limitations in the AI's ability to provide truly graduated feedback. For one, the AI sometimes made mistakes in the sequencing of advice, jumping directly from highly implicit hints to explicit corrections, bypassing the crucial intermediate steps that gradually build a learner's understanding. This is particularly problematic as it disrupts the theoretical framework of the Zone of Proximal Development, where the goal is to gently guide the learner from their current capabilities to new levels of understanding. Additionally, the AI occasionally used language or technical terminology that was beyond the comprehension level of the undergraduate students, thereby defeating the purpose of a graduated approach. While the AI's feedback was generally valuable, these inconsistencies highlight areas for refinement, particularly in aligning the tool's capabilities with established educational theories and pedagogical practices. Overall, the technology shows promise but requires further calibration to truly mimic the progression of human-aided language learning.

5.3 Use Case Three: Content-Focused Writing

In the third use case, the same twenty-eight computer science majors who participated in Use case 1 used ChatGPT to explore the similarities and differences between two distinct computer science concepts. Learners selected concepts, such as machine learning and data mining, front-end and back-end development, and Python and JavaScript. Students asked ChatGPT to create a list of the similarities and differences for their paired concepts. After receiving these lists from the LLM, students use them as the foundation for crafting a paragraph that compares and contrasts the two concepts. Once the students had completed the initial draft of the paragraph, they submitted them to ChatGPT for feedback. However, unlike the previous instances where the focus was largely on linguistic aspects, this time students requested content-specific advice. This targeted approach allows students to fine-tune not just their language skills but also their understanding of complex computer science topics. By doing so, they gain a grasp of the subject matter while also honing their ability to communicate effectively in a specialized domain.

The outcomes from this use case yielded mixed results. One striking observation was the significant variation in the quality of the feedback provided by ChatGPT. While some students received insightful comparisons that enriched their understanding of the paired concepts, others received lists that were less precise and occasionally featured repetitive points. This inconsistency could be attributed to a lack of specialized training for ChatGPT in the area of computer science, suggesting that the tool might benefit from a more subject-focused fine-tuning to improve its efficacy. Another issue was ChatGPT's tendency to rephrase rather than offer truly differentiated points, causing some lists to contain repetitive or redundant information.

Moreover, a common misunderstanding arose when the LLM produced answers in the language that the prompt was initially given in, rather than in the target language the students were aiming to practice. For instance, if a student asked a question in Japanese but intended to receive an answer in English to further practice their English skills, the LLM often responded in Japanese. This resulted in missed opportunities for language practice and necessitated extra steps to align the feedback with the educational objectives.

Overall, while ChatGPT showed promise as a tool for content-specific writing in computer science, these inconsistencies point to areas where further development is needed. Specifically, there may be a need for more refined prompt engineering and subject-specific training to better tailor the AI's capabilities to educational settings focused on both linguistic proficiency and specialized knowledge.

5.4 Use Case Four: Teaching Multiplication

In another interesting use case, four aspiring mathematics teachers, who were also computer science majors, used ChatGPT to explore various methodologies for teaching multiplication. The teachers were first-language Japanese speakers with B2 CEFR proficiency in English. Given the overarching objective to create an educational poster, the four undergraduates utilized ChatGPT to gather insights into diverse teaching strategies, from the traditional multiplication table approach to more interactive techniques like lattice multiplication (Baccaglini-Frank, 2023) or using manipulatives (Bartolini & Martignone, 2020), such as counters, arrays and Cuisenaire rods (Abreu-Mendoza, 2021). After conducting this research with the AI, they synthesized the information and incorporated it into their poster designs. These posters not only served as visual teaching aids but also became reflective tools for the aspiring teachers themselves, allowing them to critically evaluate the pros and cons of different instructional methods. By integrating AI-assisted research into their project, the aspiring teachers were better equipped to create resourceful and comprehensive educational materials, setting the stage for their future careers in mathematics education.

Further enriching this use case was the way in which they engaged with ChatGPT's outputs. Rather than taking the AI's suggestions at face value, they entered into a dialectical process with the technology, challenging its recommendations and seeking clarifications to deepen their understanding of the methodologies in question. The trainee teachers also used the AI to simulate student queries, mimicking potential questions they might face in a classroom setting. This gave them a chance to explore how well different methodologies would hold up under scrutiny, thereby fine-tuning their own pedagogical reasoning.

By incorporating ChatGPT into their project, the aspiring teachers expanded their pedagogical horizons and gained practical experience in leveraging technology for educational purposes. While the tool was not without its limitations—some found that the AI's grasp of intricate educational theories was not as nuanced as a human expert—the overall experience shed light on the transformative potential of AI in shaping future teaching and learning landscapes.

6. POTENTIAL EDUCATION APPLICATIONS FOR GENERATIVE AI

Generative AI has significant unleashed potential in education, with many areas underexplored. The four key areas that will be discussed further are the realities of implementing AI in educational settings, the provision of real-time feedback to students, the role of AI in fostering creativity, and the impact of creativity on AI's educational applications.

For instance, generative AI could be used to develop immersive learning experiences in virtual, augmented or mixed reality (De Freitas & Neumann, 2009; Russell & Kuensting, 2021). Imagine a scenario where AI-driven virtual tutors guide students through historically significant events, scientific phenomena, or complex mathematical concepts within a simulated environment. By dynamically generating relevant content and interactions, generative AI can facilitate personalized and experiential learning, allowing students to explore, experiment, and interact with subject matter in ways that were previously unattainable.

Real-time feedback is another frontier where generative AI can make a transformative impact. While traditional assessments provide feedback after the fact, AI has the potential to offer immediate and tailored feedback to students as they engage with content and assignments. By analyzing students' responses and interactions, AI models can provide insights, pointing out strengths, identifying misconceptions, and suggesting alternative approaches. This dynamic feedback loop has the potential to enhance student understanding and metacognition, fostering a more iterative and effective learning process.

Generative AI also holds the promise of fostering creativity and collaboration in education. Through AI-powered co-creation platforms, students can collaborate with AI models to generate ideas, stories, or multimedia projects. This collaborative approach not only sparks creative thinking but also exposes learners to diverse perspectives and prompts, expanding the breadth of their learning experiences.

Additionally, the personalization of education can be further enriched by generative AI. While current adaptive learning systems tailor content based on a learner's progress, generative AI can take personalization a step further by generating content that aligns precisely with an individual's learning style, pace, and preferences. This level of granularity could lead to truly individualized learning pathways that accommodate diverse needs and motivations.

As we chart the course for the future of generative AI in education, collaboration between educators, researchers, and AI developers is pivotal. By fostering interdisciplinary dialogue, we can envision innovative applications and design ethical frameworks that guide the development and deployment of AI technologies in education. It is imperative that the potential risks and challenges, such as bias, data privacy, and the preservation of human-centered pedagogy, are considered alongside the benefits to ensure a responsible and effective integration of AI into the educational landscape.

7. CONCLUSION

Generative AI offers an unprecedented opportunity to personalize and enrich the teaching and learning experience, reflecting the potential outlined in various learning theories. As we continue to explore the capacities of this technology, it is essential to consider its applications through the lenses of these educational frameworks, ensuring that we capture the full spectrum of its pedagogical potential ethically, pedagogically, and practically.

The behaviorist aspects of generative AI, as it provides immediate feedback, can be seen as a digital embodiment of reinforcement learning, promoting a responsive environment that is closely tailored to individual progress. From the cognitivist perspective, generative AI assists in information processing, a clear nod to the theory's focus on the inner workings of the mind, enabling problem-solving and the adaptation of learning experiences to the cognitive levels of learners. Generative AI's role extends to constructivism and social constructivism, where it not only supports hands-on, problem-based learning experiences but also fosters social interactions, aligning with the social constructivist belief in the importance of social contexts and interactions in knowledge construction. Moreover, generative AI acts as a critical node in a learner's network, echoing connectivism's emphasis on the learning potential within a networked, digital world.

This chapter contributes to these ongoing discussions by shedding light on the positive impacts of generative AI on educational material development and learning mediation. Generative AI's ability to comprehend and adapt to various subject domains empowers educators to transcend conventional content limitations, enabling them to provide tailored and enriched educational materials. By automating intricate categorization tasks and generating pertinent examples, this technology not only streamlines the content creation process but also nurtures a deeper understanding of complex subject matter.

While AI-generated sentences can serve as valuable exemplars, they might lack the cultural and contextual considerations that human-authored materials inherently possess. Additionally, the selection of sentences may inadvertently reinforce certain biases or linguistic patterns present in the training data of the AI model. Therefore, a balanced approach that combines AI-generated content with expert curation is crucial to ensure a comprehensive and culturally sensitive language learning experience. As we stand on the threshold of a new educational era, we must integrate generative AI with consideration of these learning theories, ensuring ethical, balanced, and equitable applications. The essence of education, with its irreplaceable human touch, is complemented and not replaced by AI, echoing the social constructivist view that learning is fundamentally a social process.

In conclusion, responsibly harnessing generative AI enables educators to craft personalized, dynamic, and engaging learning experiences, enriching the educational landscape in alignment with established and emerging learning theories. Our collective efforts to marry generative AI with the insights of these theories will be pivotal in shaping how this technology serves knowledge, growth, and lifelong learning. It is through collaboration, exploration, and responsible implementation that we will ensure generative AI becomes an enabler of educational excellence for future generations.

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