Learning in the Age of LLMs: Boosting not Bypassing the Learning Process

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1 Introduction

> Meet Tom, a high school student with a penchant for shortcuts. Homework? No problem! He casually pops his maths question into a Language Learning Model and bam! There's the answer. No effort, no thinking, just a quick fix. But what did Tom learn? Not much. He got the job done, but at the cost of understanding and critical thinking. Now, here's Sally, Tom's classmate. Sally's got the same maths problem, but she approaches it differently. She uses the LLM too, but she's asking questions, probing, testing ideas, and using it as a springboard for her thoughts. It's a dance of intellect, with the LLM as her partner. Sally's not just looking for an answer; she's learning, growing, and grasping the subject.

The stories of Tom and Sally illustrate a critical point. Large Language Models (LLMs), such as ChatGPT, (Kasneci et al., 2023) are neither inherently good nor bad for education; they are tools that can be harnessed either positively or negatively. The challenge and opportunity lie in the hands of educators, who must thoughtfully set tasks that nudge students in the direction of learning, leveraging the capabilities of LLMs to enrich learning while preserving the essential human elements of curiosity, creativity, and critical thought.

The crux of the problem is that traditional methods of learning, such as setting essays to encourage (or force) students to read, process, and write can be bypassed. This has always been the case since other students could be coerced into completing essays or more recently essays could be purchased from paper mills. However, the rise of LLMs has given students an effort-free, cost-free option, which is an attractive proposition for those aiming to coast through their school or university courses. These students not only miss out on the opportunity to learn, but their teachers are forced to provide feedback on texts that were not even written by their students.

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Here, I propose an alternative approach to setting tasks, namely structuring tasks in such a way that students are required to make an effort to process the input and the output regardless of whether students make use of LLMs.

The remainder of this chapter is organized as follows. The following section introduces four main learning theories and emphasizes that these well-established theories are equally applicable to learning with, from and through LLMs. The concepts of leaner engagement and time spent on task are then discussed with reference to learning mediated through technology. This is followed by a discussion of the benefits and drawbacks of learner use of LLMs, specifically focusing on the bypassing and the boosting of learning according to how learners interact with LLMs. The proposed model harnessing bimodal input and output is then described and explained, and a series of use cases are provided to exemplify its applicability in different university courses, namely information ethics and intermediate English.

2 Learning Theories

Behaviorism, cognitivism, constructionism, and connectivism are the four main learning theories, each offering distinct perspectives on the process of learning (Stewart, 2021). All four theories were developed prior to the widespread availability of LLMs. However, as Blake (2023) notes, these theories also apply to learning with generative artificial intelligence and LLMs. Behaviorism focuses on observable behaviors and emphasizes the role of external stimuli and reinforcement in shaping those behaviors (Fisher et al., 2021; Watson, 2017). It views learning as a product of conditioning and does not concern itself with internal mental processes. Cognitivism, in contrast, puts its central focus on the internal mental processes involved in learning, such as attention, memory, and problem-solving. It sees learning as an active process of information processing and knowledge construction within the learner's mind. Constructionism builds upon cognitivism but emphasizes the importance of creating tangible representations or constructions of knowledge, asserting that learning is most effective when learners are actively involved in constructing something meaningful (Nagowah & Nagowah, 2009). Social constructionism is an extension of this, based on the principles advanced by Lev Vygotsky (1987) and emphasizing the importance of the co-construction of meaning through a dialogic process. Connectivism, a more recent theory, extends the focus of learning to the networked digital age (Downes, 2022). It posits that learning occurs across distributed networks and emphasizes the importance of social connections, information access, and the ability to synthesize information across various domains. While behaviorism concentrates on external control of learning, cognitivism and constructionism highlight the internal cognitive and constructive processes, respectively, and connectivism emphasizes the relational and networked aspects of learning. Together, these theories provide diverse lenses through which to understand and facilitate learning, each reflecting different assumptions about the nature of knowledge, learning, and the role of the learner and environment.

3 Engagement and Time-On-Task

Engagement with learning materials and the concept of time-on-task are foundational principles within the educational process (Godwin et al., 2021). Engagement is not simply interaction with content; it involves deep intellectual involvement, curiosity, and active processing that enable learners to connect, synthesize, and critically analyze new information. This aligns with cognitivism's focus on mental processes and the internal cognitive structuring that fosters comprehension and knowledge retention. Learner engagement is a critical factor in education, with implications for student retention and degree completion (Seo & Gibbons, 2019).

The use of student-centered approaches helps to increase engagement as does enriching the learning environment using the latest technology. Chen et al. (2010) in an investigation of the impact of web-based learning technologies found a general positive relationship between learner engagement and the use of technology for learning purposes. Ullah and Anwar (2020) showed that the combination of technology, collaboration, and interaction positively influenced learner engagement among a group of 24 computer science majors. Learner engagement increases when learners are interested in the topic or task and decreases when they are not. Hu and Hui (2012) in an examination of the role of learner engagement in technology-mediated learning showed that the effects of the technology-mediated learning were mainly attributable to learner engagement. Based on a study of 120 undergraduates studying finance using interactive spreadsheets and problem files, Bertheussen and Myrland (2016) showed that learner performance in the midterm exam was strongly associated with engagement with the digital learning materials. You (2022) found that the degree of engagement with online learning materials in terms of behavioral, cognitive, and emotional input correlated with learning completion. There has been an avalanche of research on the impact of ChatGPT and other LLMs on education, with multiple studies showing a positive impact on learning. Two recent studies noted the positive impact on learner engagement (Alshahrani, 2023; de Castro, 2023).

Time-on-task, the dedicated and focused time spent on learning activities, complements engagement by allowing for a more profound exploration and reflection on the subject matter. Studies on the impact of time-on-task, in general, show a positive correlation between time spent on a task and the achievement of the learning outcome (Fredick & Walberg, 1980; Godwin et al., 2021; Kovanović et al., 2015; Scherer et al., 2015). Within the cognitivist framework, this extended engagement provides opportunities for encoding, consolidation, and application of knowledge, enhancing both immediate understanding and long-term retention. Together, engagement and time-on-task emphasize the active, conscious, and time-intensive nature of learning, underscoring the complex interplay between attention, understanding, memory, and reflection. These principles are vital for promoting intrinsic motivation, resilience, and lifelong learning skills.

Within the cognitivist paradigm, the process of learning may be conceptualized as a series of discrete, interconnected stages. The process typically commences with the attention stage, in which learners selectively focus on specific information, allowing it to enter their cognitive system. This is followed by the perception stage, in which learners interpret and make sense of the information, relating it to their existing knowledge structures. The encoding stage then involves the transformation and organization of this interpreted information into a form suitable for short-term storage. Consolidation represents the next critical phase, where information is transferred from short-term to long-term memory through processes such as rehearsal and meaningful connections. The retrieval stage allows learners to access and recall this stored information when required. Application, the stage where learners utilize the retrieved information in new contexts or problem-solving situations, reflects a more profound level of understanding and knowledge transfer. In some frameworks, metacognition is also considered, where learners engage in self-reflection, evaluation, and regulation of their learning strategies. These stages together provide a comprehensive view of the cognitive processes involved in learning, emphasizing the complex interplay between attention, understanding, memory, application, and reflection.

4 Large Language Models

Large Language Models (LLMs) represent a radical advancement in the field of artificial intelligence (Gan et al., 2023), particularly in their ability to process and generate human-like text. Utilizing intricate pattern-matching algorithms, these models can interpret and produce language with a fluency that closely mimics human communication. Their proficiency lies in analyzing vast amounts of textual data and identifying statistical patterns within the texts, enabling them to generate coherent and contextually relevant text. However, despite this remarkable capability, LLMs lack a fundamental understanding of both real-world relations (Hofkirchner, 2023; Ruis et al., 2022) and the underlying meanings of the texts they generate (Mitchell & Krakauer, 2023; Veres, 2022). Their responses are formed based on the statistical regularities in the data on which they were trained, rather than any intrinsic comprehension of the subject matter. As a result, while they can effectively mimic human language use, their outputs might not necessarily reflect a true understanding of the content or context, leading to potential misrepresentations or oversimplifications (Rudolph et al., 2023; Zhu et al., 2023). This highlights an essential distinction between human cognition and current machine learning techniques, underscoring the complexity of replicating genuine human understanding of language. In the context of LLMs, hallucination refers to instances where the model generates text that is either factually incorrect, nonsensical, or not grounded in reality, despite appearing plausible or coherent. This phenomenon, or "cognitive mirage" as Ye et al. (2023) put it, occurs because the model, while proficient in pattern recognition and language generation, lacks true understanding or awareness of real-world facts and contexts. As a result, it may produce responses that are misleading, untrue, or disconnected from the actual query or data. Hallucinations highlight the limitations of current language models in terms of their reliance on learned patterns from training data

(Ji et al., 2023), rather than on a genuine comprehension of content or the ability to discern factual accuracy.

The utilization of LLMs by students to complete assignments can have significant negative implications for the learning process. By relying on LLMs to undertake the intellectual heavy lifting, students may bypass essential stages of cognitive engagement, critical thinking, problem-solving, and creativity that are foundational to learning and academic growth. Such a practice diminishes the opportunities for students to engage with the material actively, interpret complex concepts, synthesize information, and articulate their own thoughts and perspectives. This avoidance of genuine engagement with the subject matter can lead to a superficial understanding of the content, a lack of skill development, and the erosion of academic integrity (Currie, 2023). Furthermore, it undermines the educator's ability to accurately assess a student's mastery of the subject, thereby weakening the educational system's overall efficacy. In the long term, this dependence on LLMs may stunt the development of essential skills needed for future success in higher education and professional domains, ultimately detracting from the true purpose and value of education.

Conversely, students using appropriate learning strategies can use LLMs to receive personalized instruction and enable them to understand concepts that they might not have been able to grasp studying without such assistance. These strategies invariably impact the behavioral, cognitive, and emotional investment that students make. Students can use LLMs in a multitude of ways. For instance, computer science students grappling with algorithms can leverage LLMs to clarify intricate concepts, such as sorting algorithms or data structures, through detailed explanations and examples. Students can simply input a code snippet and ask the LLM to explain the code. ChatGPT released customized versions in late 2023 that specialize in tutoring. *Creative Writing Coach* is designed to hone writing skills, *Math Mentor* is designed to help parents and tutors deal with the arithmetic and mathematic problems that school-aged students need to solve, while *Tech Support Advisor* is the go-to customized chatbot that can explain technical issues. Furthermore, LLMs can provide insights into syntax and common programming pitfalls. Due to their conversational nature, LLMs can be used for language learning and practice, which is particularly beneficial in a field like computer science where English often serves as the lingua franca. Kohnke et al. (2023) note that both teachers and learners need to develop requisite digital competencies to be able to maximize learning opportunities to support language learning.

5 Increasing Engagement and Time-On-Task

In light of the challenges posed by the utilization of LLMs, there is an urgent need to prioritize and cultivate student engagement with learning materials, emphasizing the critical process of thinking and reflection. The convenience and accessibility of LLMs can inadvertently facilitate a surface-level engagement where students merely copy and paste text, bypassing the cognitive investment that genuine learning requires.

Such practices not only hinder the acquisition of deep understanding but also foster a passive learning culture where the quest for knowledge is reduced to mere information retrieval. Engaging students in thoughtful interaction with learning materials goes beyond the mechanics of information acquisition; it involves stimulating curiosity, encouraging critical analysis, and fostering a genuine desire to explore and understand complex ideas. It requires educators to craft learning environments and activities that actively resist the temptation to simply rely on technology's capabilities, and instead, inspire students to grapple with concepts, ask probing questions, and engage in meaningful dialog with the content. This commitment to authentic intellectual engagement is not only vital for preserving the integrity of the educational process but also for empowering students with the cognitive tools and skills necessary for lifelong learning and success.

6 Task-Based Learning

Traditional education may employ a task-based approach to facilitate learning, where a task is a specific activity or assignment given to students that requires them to apply their knowledge and skills to accomplish a particular goal. These tasks may vary in complexity and scope, ranging from simple exercises like essays or reports to comprehensive projects. They can be subdivided into smaller, manageable components, helping students focus on specific aspects of the broader task, such as breaking down complex tasks into smaller parts to allow for step-by-step completion. This method of subdivision is integral to task-based learning, an approach that emphasizes learning through engagement with real-world tasks. Task-based learning encourages active participation and mirrors real-world situations (Blake, 2020), promoting skills like problem-solving and critical thinking, making it an essential component of modern education practices.

Learning during task-based activities occurs throughout the entire process, encompassing various stages of task completion. It starts with the introduction of the task, where students become engaged with the problem or goal at hand. As they plan and strategize how to approach the task, they engage critical thinking and problem-solving skills, and learning occurs as they identify the knowledge and skills required to proceed. During the execution of the task, students apply what they have learned, refine their understanding, and gain practical experience, all of which contribute to the learning process. Feedback and reflection on the completed task provide additional opportunities for learning, as students assess their performance and understand how their efforts contributed to the outcomes. Thus, task-based learning offers continuous learning opportunities that span from the initial understanding and planning stages through to execution and reflection, creating an engaging and holistic educational experience.

In traditional education, learners apply knowledge and develop the requisite skills to complete tasks, and thorough this cognitive struggle, students have the potential to learn. The rubrics of the task could be considered as input while the product created

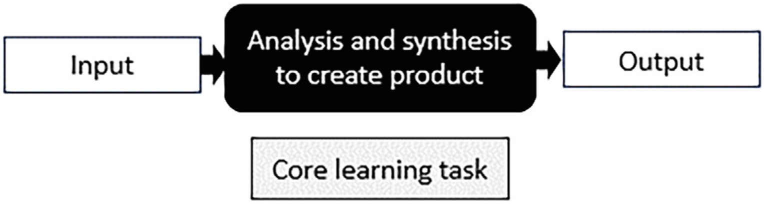


Fig. 1 Traditional learning model

by the learner is the output. The process that the learners engage it to create the product is the core learning task. This can be represented visually as shown in Fig. 1.

If students use LLMs or other automated tools to solve problems for them without aiming to learn, they lose several crucial aspects of the learning process. Figure 2 shows how the learning phase may be completely replaced by AI tools. In this scenario, the learner simply inputs the rubic into the AI interface and submits the output. By relying on automation, they miss the opportunity to engage in critical thinking and problem-solving, undermining the development of essential cognitive skills. Without actively grappling with the task, students may fail to understand underlying concepts, leading to superficial understanding. They also lose the chance to apply theoretical knowledge practically, impeding skill development, and they may skip the essential reflection and self-assessment stage, hindering personal growth.

Ethical considerations and academic integrity may also be compromised if students rely on these tools in contexts where independent work is expected (Qadir, 2023). Furthermore, bypassing the learning process in favor of automation may diminish students' intrinsic motivation and engagement with the subject. In summary, relying on LLMs without the intention of learning bypasses the core principles of task-based learning, leading to a shallower and less enriching educational experience. Educators dictate that AI tools should not be used, but according to Weale (2023), this is "neither feasible nor advisable" (n.p.). However, a more effective solution would be to set a task so that learners must engage with the materials even if they use AI. This both embraces new technologies and removes the difficulty of evaluating whether learners surreptitiously made use of AI. Sullivan et al. (2023) highlight the necessity for educators to bring their pedagogy and assessments in line with the era of freely-available generative AI tools by focusing on critical thinking.

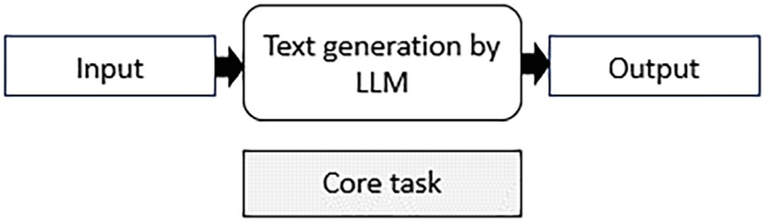


Fig. 2 Traditional model in which LLM replaces opportunity to learn

Although AI tools, and LLMs in particular, are powerful, they cannot (yet) deal with many tasks. Malinka et al. (2023) suggest focuses on these weaknesses by setting tasks that require practical world knowledge which is a weakness of LLMs and using images to present information making it more difficult for LLMs to be used directly. The initial release of ChatGPT only allowed textual input and textual output. This was the inspiration for a bimodal input and output approach.

7 Bimodal Input and Output

Current state-of-the-art LLMs, such as ChatGPT and Bard, rely primarily on the input from textual prompts to generate responses. Should educators set assignments using video, audio or images, then students who want to use generative AI need to transfer the modality of the assignment into a suitable textual form. This may be a simple chore when the task is simply presented as an image of written text. Students could simply retype the assignment themselves or use optical character recognition to automatically extract the text from the image. However, if assignments are set using two different input sources, such as an audio file and image, then students need to decide who to combine the input information so that the LLM can generate the most appropriate response. Likewise, requiring students to submit their assignment in a different modality ensures more active participation by the student. For example, requiring students to submit video slideshow with annotations forces students to engage with the output of regular LLMs. There are, naturally, AI solutions to this, such as using an AI slideshow generation tool, such as Beautiful. AI and using AI text-to-speech software, such as PlayHT and AI video creation tools like Sora. However, even using these tools, students still need to engage with the various generated outputs. As new AI tools and features evolve, the parameters used for the bimodal input and output may need revision to ensure that learners need to process any AI-generated output prior to submission.

Setting tasks with bimodal input and output can, therefore, be a valuable approach to bolster, rather than bypass, the learning process. By requiring students to think carefully about how to synthesize information to create a prompt for an LLM and then transforming the output into a required mode or format, they are actively engaged in complex cognitive activities. This process demands a deep understanding of the content, as well as the ability to analyze, interpret, and apply the information. The bimodal approach encourages students to critically evaluate the information provided by the LLM and creatively adapt it, enhancing both analytical and creative thinking skills. The necessity to understand the input and thoughtfully convert the output fosters a higher level of engagement with the task, driving students to develop a more nuanced understanding of the subject matter. This method goes beyond merely using the LLM as a tool for completing a task, instead integrating it into the learning process, turning the use of advanced technology into an opportunity for enriched learning (Rahman & Watanobe, 2023). It is somewhat akin to encouraging students to create

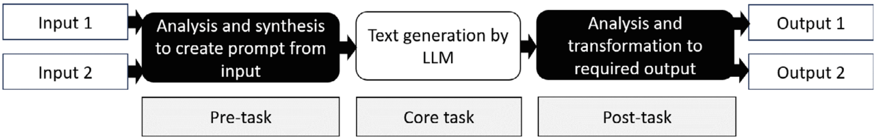


Fig. 3 The learning phases using bimodal input and output model with LLMs

a cheat sheet, which despite its name forces learners to organize and summarize, creating a prime learning opportunity (Erbe, 2007).

In a traditional task-based learning structure where learning may occur throughout core task, introducing an LLM to complete the core task significantly shifts the dynamics of the learning process. Figure 3 provides a visual representation of the learning stages for the bimodal input and output approach that integrates Language Learning Models (LLMs). The emphasis now moves to the pre- and post-task stages (shaded in black), turning the learning experience into a more intricate engagement. In the pre-task stage, students must analyze and synthesize the problem to formulate an appropriate prompt for the LLM, enhancing comprehension and analytical skills. Although the core task stage sees a reduction in hands-on problem-solving, it introduces a novel learning point, fostering an understanding of how technology interfaces with human cognition. The post-task stage then becomes vital, as students critically evaluate the LLM's output and transform it into the required format, increasing their engagement with higher-order thinking skills like evaluation and synthesis. This shift from rote execution to a more complex interplay between understanding, critical evaluation, and creative transformation encourages a deeper engagement with both content and technology, fostering a richer learning experience that leverages the capabilities of the LLM while still prioritizing essential human cognitive and analytical skills. The following section looks at three case studies of how this bimodal input and output model can be harnessed.

8 Case Studies: Hypothetical and Practical Implementation of Bimodal Approach

The use of case studies to test the implementation of a bimodal approach incorporating both hypothetical and practical scenarios provides a robust framework for deeply understanding its applicability, potential challenges, and outcomes within diverse educational contexts. Case studies allow for an in-depth exploration of how the method can be implemented and the various factors affecting its efficacy. The hypothetical case study serves as a conceptual proof-of-concept, presenting an exploration of the method's potential impact and limitations without the constraints of real-world implementation. In contrast, the practical case studies, grounded in actual educational settings, furnish empirical evidence of the method's practicality, effectiveness, and adaptability to different educational environments and learner needs.

This complementary approach not only highlights the versatility and potential of the new method but also provides a comprehensive understanding that is critical for educators, researchers, and policymakers aiming to innovate and improve educational practices. Three case studies are presented.

8.1 Hypothetical Case Study 1: Video and Manga Input with Animated Slideshow Output

An assignment focused on information ethics, such as discussing the privacy and security concerns of Social Networking Services (SNS), can be creatively transformed using a bimodal input approach. Instead of a traditional written prompt, students could be provided with both a video recording outlining real-world scenarios of privacy breaches and a manga strip illustrating fictional or exaggerated concerns related to SNS security. This combination would require students to synthesize information from two diverse formats, engaging multiple senses and cognitive processes. The visual and narrative elements of the video and manga would encourage students to think critically and creatively about the ethical dimensions of privacy and security in a way that a textual prompt might not. For the output, students could create an annotated slideshow that integrates insights derived from both the video and the manga. This would force them to translate their understanding into a new format, further challenging their analytical and synthesis abilities. By employing multimedia inputs and requiring a complex, multifaceted output, the assignment would not only address the core subject of information ethics but also enhance students' abilities to engage with and transform information across different modalities, making the learning experience more engaging, immersive, and reflective of the multifaceted nature of modern communication.

8.2 Case Study 2: Verbal Input with List of Topics with Annotated Essay in Specified Format

By providing input in the form of teacher explanation, there is no written record to be transformed into a prompt. Thus, students who want to use this information in a prompt need to remember and type the information. A downside to this is that students who have difficulty understanding instructions may be disadvantaged. One way to ameliorate this is to allow students to discuss the task together to ensure that all students understand the task at hand. Comprehension of the instructions could also be confirmed using concept check questions. Different topics can be set for each student. Figure 4 shows the first eight topics for an annotated essay set in an information ethics course. As there is only the topic and a question, simply using this a prompt will not produce output in the required format. Learners were required to produce an annotated essay. Although the essay may be thought of as textual, it comprises two parallel texts: the essay itself and the annotations. To ensure that students engage with the course materials, they were required to follow precise instructions when drafting the essay (See Fig. 5 for an extract from one exemplar essay). These included citing relevant units from course, related to the topics discussed colored red and showing ethical concepts in bold. The annotations name the type of reasoning and where possible show the logical argument.

Activity 7: Topics for annotated essay 📖

Select one topic from this list. Each student must have a different topic.

1. The Ethical Implications of Data Mining: Should companies be allowed to mine customer data without explicit consent?
2. Right to Be Forgotten vs Public Right to Know: Striking a balance between personal privacy and the public's right to information.
3. Open Source Software: Ethical considerations in making software freely available for modification and distribution.
4. Artificial Intelligence and Bias: The ethical implications of machine learning algorithms that reinforce societal biases.
5. Deepfakes and Information Integrity: How deepfakes pose ethical challenges to journalism, politics, and personal identity.
6. Ethical Hacking: Is ethical hacking genuinely "ethical" or does it create more problems than it solves?
7. Net Neutrality: Why it is ethically necessary to ensure equal access to internet services.
8. Ethics of Facial Recognition: An argument in favor of or against the increasing use of facial recognition technology in public spaces.

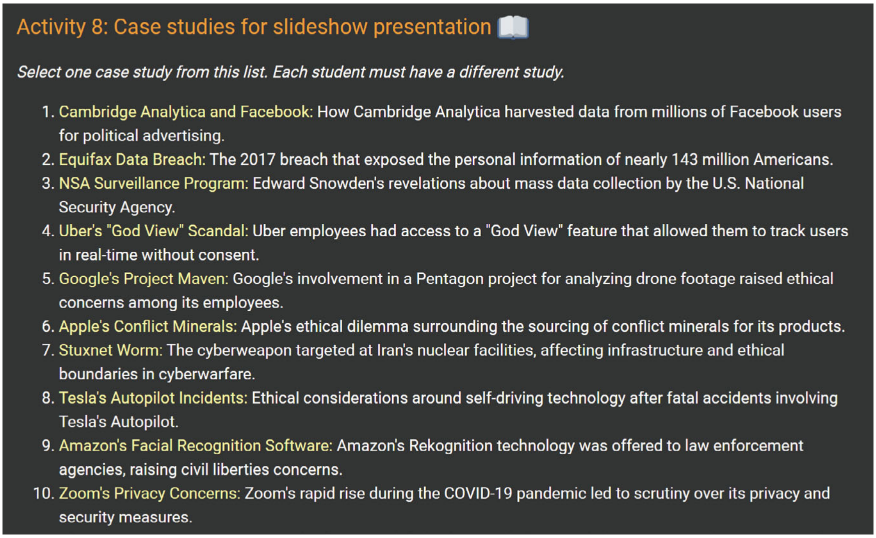
Fig. 4 First 8 of 25 essay topics

1.2 *Overview* This essay presents three arguments in support of the actions of the student. This ethical examination of the student action offers one possible lens through which this scenario can be analyzed.	
2. Arguments 2.1 *Claim: Unauthorized access is unethical.* The evidence stems from the university's stringent policy against unauthorized access to its systems. The policy is a reflection of legal and institutional norms (U1) that categorize unauthorized access as unethical and illegal. The ethical framework here is straightforward and follows **deontological ethical frameworks** (U2), such as **Kantian ethics** [1]. All unauthorized access to systems is prohibited. The student engaged in unauthorized access. Therefore, the student's action is prohibited.	Claim 1 Deductive reasoning (U1) [$P \wedge Q \rightarrow R$] Can be stated as CD (U2).

Fig. 5 Extract from annotated essay showing required format

8.3 Case Study 3: Slideshow Exemplar and Student-Selected Topic with Slideshow Presentation Output.

In the same information ethics courses, students were required to research a case study. Students selected a topic from a list, an extract of which is shown in Fig. 6. This time there is no question, but simply the name of the case study and an introductory sentence to provide a brief outline of the issue related to information ethics. Students were required to investigate this topic. The bimodal input therefore stems from the topic and the web search. Students were shown an exemplar presentation (see Fig. 7) so that they could understand the requirements. At the time, the web-interface version of ChatGPT available in Japan was unable to access Bing to search the web directly and so students had to source suitable texts themselves. As the required output was a slideshow presentation, students had to create a slideshow, and give a presentation in small groups. Students had the option to present live or create a video recording of their presentations and the subsequent question and answer sessions. The bimodal output was the slideshow (which in fact required text, images, and speaker notes) and the actual presentation, most of which was recorded using the recording feature within Zoom and submitted as a video.



Activity 8: Case studies for slideshow presentation

Select one case study from this list. Each student must have a different study.

1. Cambridge Analytica and Facebook: How Cambridge Analytica harvested data from millions of Facebook users for political advertising.
2. Equifax Data Breach: The 2017 breach that exposed the personal information of nearly 143 million Americans.
3. NSA Surveillance Program: Edward Snowden's revelations about mass data collection by the U.S. National Security Agency.
4. Uber's "God View" Scandal: Uber employees had access to a "God View" feature that allowed them to track users in real-time without consent.
5. Google's Project Maven: Google's involvement in a Pentagon project for analyzing drone footage raised ethical concerns among its employees.
6. Apple's Conflict Minerals: Apple's ethical dilemma surrounding the sourcing of conflict minerals for its products.
7. Stuxnet Worm: The cyberweapon targeted at Iran's nuclear facilities, affecting infrastructure and ethical boundaries in cyberwarfare.
8. Tesla's Autopilot Incidents: Ethical considerations around self-driving technology after fatal accidents involving Tesla's Autopilot.
9. Amazon's Facial Recognition Software: Amazon's Rekognition technology was offered to law enforcement agencies, raising civil liberties concerns.
10. Zoom's Privacy Concerns: Zoom's rapid rise during the COVID-19 pandemic led to scrutiny over its privacy and security measures.

Fig. 6 List of case studies for students to select from

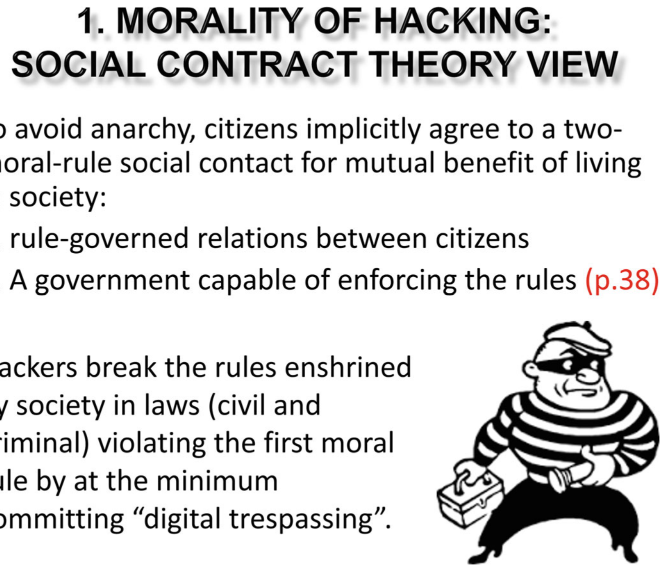


Fig. 7 Example slide from exemplar slideshow

9 Conclusion

The integration of Language Learning Models (LLMs) in educational settings offers promising avenues for enhancing learning, but it also underscores the necessity to thoughtfully augment or ameliorate their use. While LLMs have the potential to significantly enrich the learning experience by fostering critical thinking, synthesis, and engagement with complex cognitive processes, there is a risk that improper utilization may bypass essential learning points, leading to a superficial understanding. By carefully designing tasks and assessments that incorporate the usage of LLMs in a way that complements human cognitive skills (Sullivan et al., 2023), educators can leverage the technology to expand learning opportunities without diminishing essential human-centered educational values. Such an approach requires a balance between the benefits of automation and the core principles of critical thinking, problem-solving, and creativity. Therefore, a conscientious and methodically designed integration of LLMs, such as the bimodal approach described earlier, becomes vital to ensure that the use of these advanced tools bolsters, rather than hinders, the fundamental goals of education.

The process of converting different modalities into textual forms for LLMs and vice versa resonates with the main learning theories. From a cognitivist perspective, this task demands internal mental processes such as attention, perception, and memory. Students must comprehend and mentally process the content in one modality and translate it into another (e.g., textual), reflecting the cognitivist focus on how information is received, organized, stored, and retrieved by the mind. The constructionist approach is evident when students actively construct new knowledge by integrating different modalities. The act of creating an assignment in a different format, such as a video slideshow, requires them to apply their understanding in a tangible form, embodying constructionism's emphasis on learning through making. In terms of connectivism, the use of LLMs and other AI tools reflects learning as a networked process. Students must navigate and connect diverse information sources, including LLM outputs, AI slideshow tools, and text-to-speech software. This approach aligns with connectivism's view of learning as a distributed process across various digital platforms. Moreover, the bimodal approach aligns with the principles of social constructionism, particularly when students are required to collaborate or discuss their interpretations and methods for converting modalities. The dialogic process of co-constructing understanding with peers or educators mirrors Vygotsky's emphasis on social interaction in learning.

It should also be noted that this chapter focused on assignments in which students produce essays and presentations. The bimodal approach may be unsuitable for or need to be adapted for different types of assignments. Although there are cogent theoretical arguments in support of a bimodal approach, experimental and empirical evidence is needed in order to create a more persuasive argument for its adoption. However, in the meantime, integrating LLMs with a bimodal input and output approach in learning environments can be seen as a versatile pedagogical strategy. It not only aligns with multiple learning theories but also enriches the learning experience by fostering critical thinking, creativity, and problem-solving skills. Such an approach ensures that the technology serves as a catalyst for deep learning rather than a shortcut to task completion.

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