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Article

From Artificial Intelligence to Real Dummies

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Abstract: As educational policies increasingly advocate integrating generative artificial intelligence (AI) into teaching practices, important questions arise about its effect on students' cognitive development. By observing how students use large language models (LLMs), we can see their potential to disrupt traditional learning frameworks, such as Bloom's Taxonomy. This article explores how AI influences students' work habits, knowledge acquisition, and cognitive skills based on two years of observations of 70 first-year computer science students in an 180-hour programming course. The results suggest that generative AI could undermine the hierarchical structure of Bloom's Taxonomy by enabling students to bypass essential cognitive processes, such as comprehension, application, and analysis. This allows them to replace their personal efforts with AI-generated results. These findings raise concerns about the erosion of critical thinking and problem-solving skills, which could reshape educational goals established since the 1960s. Rather than taking a position for or against the use of AI, the article aims to stimulate debate about its long-term implications for developing and managing students' knowledge and skills. The article highlights the need for teachers and policymakers to address ethical challenges and strategies that ensure AI enhances, rather than replaces, cognitive engagement in learning. After an introduction, Chapter 2 provides an overview of Bloom's taxonomy. Chapter 3 explains the principles of how LLMs work. The next chapter describes how students use LLMs based on behavioral observations. Before concluding with the importance of policy decisions to be made in the coming years, Chapter 6 discusses how LLMs can influence teaching methods.

Keywords: Generative AI; Education; Behavior

1. Introduction

One of the key objectives of the field of educational sciences is to develop a systematic approach to classifying and prioritizing the diverse objectives of learning. This classification allows for the construction of stages of increasing complexity in the cognitive development of individuals. In 1956, B.S. Bloom et al. put forth a preliminary taxonomy of cognitive objectives, with the principal objective of developing tests and examinations [1]. Although revised in 2001 by Anderson and Krathwohl and occasionally the subject of debate [2, 3], this classification has had a significant impact on the teaching of higher-order thinking, moving students away from rote learning and superficial understanding. The integration of new technologies, such as calculators and computers, into teaching practices has been a long-standing objective of the education sector. More recently, the advent of digital technology and the development of the Internet have provided new avenues for accessing information, which have been harnessed by educators to enhance learning outcomes. Thus far, this transformation has been techno-centric, with politicians espousing the view that the use of interactive whiteboards, search engines, computers, or tablets would markedly enhance students' interest in education and facilitate teachers' work [4,5]. Thomas Edison predicted in his day that cinema would replace textbooks, but due to mistrust on the part of some and lack of vision on the part of others, computers and digital technology in the broadest sense have struggled to gain a foothold in the world of education. To make up for this delay, action plans have proliferated without coherence, consultation, or support. Qualitative research has shown that teachers find it difficult to use computers as teaching aids in their classrooms. Using the computer as a tool for teaching and learning is not a "brilliant" solution for educating students, but it's a breakthrough. How and for what purposes should digital technology be used in the classroom, so that teaching and use are not completely outdated in the years to come [6–8]? But this question may raise other questions:

– Are we designing a school around computers (i.e., transforming it) or simply introducing computers into the school (i.e., integrating new knowledge)?
– Can we imagine how IT will change our basic skills: reading, writing, calculating, thinking, and criticizing?
– What can be done to anticipate these changes?

Even if some people date AI back to the 1950s, or even a little earlier, with Alan Turing, who wondered whether machines could think. (Incidentally, in his imitation game test, Turing shifted the problem by replacing language with thought. Do we always say what we think???) It must be said that, after several winters, some of them very harsh, AI is now at the forefront of the scientific and economic scene, because for two years we've been talking about ChatGPT and your washing machine, your hearing aids and your vacuum cleaner have also become intelligent. The use of LLMs (Large Language Models) and AI in general in education wasn't long in coming. C. De La Higuera and J. Iyer propose several ways of thinking about the use of artificial intelligence in education in an open textbook of more than 200 pages [9]. The document remains an ode to the massive and immediate introduction of AI into our education, even if some dystopian aspects are evoked. The authors' conclusion could be summed up in a techno-centric approach: "It took us 40 years to introduce computers into our classrooms, let's not take another 40 years to introduce AI". It's a pity that the authors didn't take the learner's point of view and ended up with a very techno-centric version. From the teacher's point of view, this document presents the impact of GAI tools on course preparation, classroom management, and the possibility of automating certain tasks such as correction. From the learner's point of view, the justification for using these tools seems to focus more on the reinforcement of knowledge, personalization of work, and self-learning. Little or no attention is paid to the impact on learners' cognitive and metacognitive skills. What happened to our beautiful Bloom's Taxonomy pyramid that has guided our learning objectives for 70 years? What kind of students will we be educating if AI and GAI are massively adopted as pedagogical tools?

This article offers some food for thought, not based on an academic study, but on observing how our students acquire and use GAIs. For the last two years I've been observing the behaviour of my students on the Learning to Programme course. The number of students observed each year is 35, so 70 people over the last 2 years. The teaching volume is 180 hours between September and May. After a reminder of Bloom's taxonomy and the operating principles of LLMs, I'll present some cases of GAI use that could be described as deviant, and the impact this might have on students' cognitive and metacognitive learning.

My observation, more than a hypothesis, is: Generative AI seems to weaken the effectiveness of Bloom's classification method?

2. Background to the Discussion

2.1. Bloom's Taxonomy

Bloom and his collaborators in the 1950s developed this widely used pedagogical framework for classifying students' learning levels [1]. It enables educators to design learning objectives, assessments, and instructional activities that promote the deep understanding and practical application of knowledge. Bloom's taxonomy is divided into three main domains of learning, each with its own hierarchical levels, although educational studies tend to emphasize the domain of knowledge.

(1) The cognitive domain (**Figure 1**): This domain focuses on the mental processes that are related to knowledge. It is made up of six levels: knowledge, comprehension, application, analysis, synthesis, and evaluation. These levels range from the simple memorization of information to the generation of new ideas and critical evaluation.

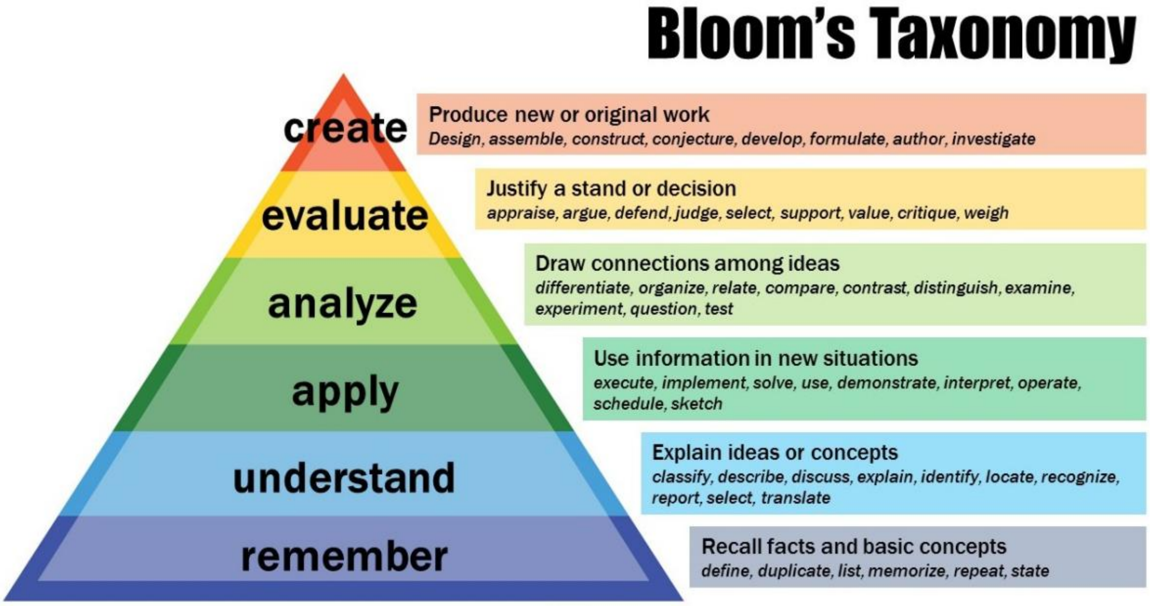

Figure 1. Bloom's Levels of Learning.

- **Memorize/Knowledge**: Recall facts, basic concepts, and information. Example: memorizing historical dates.
- **Understanding**: Ability to explain ideas or concepts. Example: summarize a text.
- **Apply**: Using knowledge in new situations. Example: solving mathematical problems by applying formulas.
- **Analyze**: Breaking down information into smaller components to understand its structure. Example: identifying the parts of an argument or text.
- **Evaluate**: Identify the advantages and disadvantages of possible courses of action.
- **Synthesis/Creation**: Suggest alternatives, different approaches, original solutions.

(2) **Affective** domain: The affective domain describes learning goals that emphasize a feeling, emotion, or degree of acceptance or rejection [10]. Affective objectives range from simple attention (to a selection of phenomena) to complex qualities of character and awareness. Objectives are expressed as interests, attitudes, appreciations, values, sets of emotions, or prejudices. This second area can be divided into five categories:

- **Receiving**: It means tolerating and being aware of the existence of certain ideas or phenomena. For example: accepting, listening, reacting, comparing.
- **Responding**: It's about forcing yourself to put ideas into action by actively responding to them. For example: to comply with, to recommend, to volunteer, to dedicate one's free time.
- **Appreciate**: The desire to be perceived by others as someone who values ideas.
- **Organizing**: To link a value to those already held, while remaining internally coherent. For example: discussing, theorizing, and investigating.
- **Characterize**: To characterize means to act consistently according to acquired values. Examples: revise, demand, avoid, manage, solve.

(3) The **psychomotor** domain includes physical movement, coordination, and the use of motor skills. We are not far from the form of kinesthetic intelligence defined by Howard Gardner [11,12]. However, the development of these skills requires practice and is measured in terms of speed, precision, distance, procedures, or execution techniques. Thus, psychomotor skills range from manual tasks, such as digging a ditch or washing a car, to more complex tasks, such as operating a complex machine or dancing. The domain is subdivided from simple to complex:

- Perception (sensory guidance of motor activity)

- Preparation (feeling ready to act)
- Guided response (beginning to learn complex skills)
- Mechanism (development of a basic skill)
- Complex open response (execution with advanced skill)
- Adaptation (modifying movement to suit specific circumstances)
- Origin (creation of situation-specific movements)

Educational sciences are often criticized for the propagation of relatively persistent pedagogical myths: learning styles, multiple intelligences, educational differentiation, Dale's hierarchy, and many others. First, this taxonomy is a classification of learning objectives, often used to calibrate assessments, differentiate, etc. There are other similar taxonomies, such as the SOLO taxonomy [13], and Gagné's taxonomy (much more interesting and scientifically well-founded) [14,15]. Bloom's taxonomy has long been criticized because it is not clear what principles or ideas led to its development. The main criticisms are:

(4) Being relatively old, i.e., conceived at a time when there were no digital devices or pedagogical innovations.
(5) To propose a hierarchy of learning objectives and mechanisms; however, more recent approaches (e.g., neurocomputational or neurocognitive) have since shown that these objectives and mechanisms are not so much hierarchical as pyramidal.
(6) Not considering the characteristics of learners and teachers.
(7) Disregarding contextual elements (political, economic, physical, social environments, etc.) and operating as if objectives and mechanisms were independent of all these factors.
(8) To be, for some, a "myth" based solely on the vague intuitions of its creator, with no objective, tangible data to differentiate the different levels of the taxonomy.
(9) To be a model focused on learning, not on learners (and even less on teachers).

Attempts to revise the taxonomy, such as Anderson's revised taxonomy of 2002 [3], suffer from the same problem: it's not at all clear why the different levels of the hierarchy are what they are, let alone why they are organized in that order.

However, as Bloom's work is still a reference in teacher training institutions (INSPE: french teacher training institute), it was interesting to assess its resilience to the problem of introducing AI into the classroom. We could have done this with other tools (SOLO or Gagné's taxonomy) and the results would certainly have been the same.

3. LLM-Type Generative AI

Large Language Models (LLMs) are a class of artificial intelligence models designed to understand and generate text in natural language. Their development has accelerated dramatically in recent decades, thanks to major advances in deep learning and natural language processing (NLP).

The first attempts at language modeling date back to the 1950s and 1960s, with the advent of computer science. Programs such as ELIZA, developed by Joseph Weizenbaum in 1966 [16], used pre-defined scripts to simulate simple conversations. In the 1980s and 1990s, statistical models such as Hidden Markov Models (HMMs) and n-grams became dominant in natural language processing. These models relied on probabilities to predict the next word in a given sequence based on previous words [17]. The advent of neural networks and deep learning in the 2010s marked a significant advance. Recurrent Neural Networks (RNNs) and Long-Term Short Memory Networks (LSTMs) have made it possible to capture sequential dependencies in text data more effectively [18]. Vaswani's 2017 paper "Attention is All You Need" introduced the transformer architecture and revolutionized the field [19]. Unlike RNN and LSTM, transformers use attention mechanisms to enable more efficient parallel processing of sequences. The Generative Pretrained Transformer model series introduced by OpenAI has demonstrated the power of transformers. GPT-2, released in 2019, and GPT-3, released in 2020, have 1.5 billion and 175 billion parameters respectively, demonstrating the effectiveness of large-scale models in generating coherent, contextually relevant text [20,21].

3.1. How Do LLMs Work?

3.1.1. Transformer Architecture

Transformers use a two-part architecture: the encoder and the decoder. However, some models like GPT use only the decoder. This is how the architecture works:

- **Encoding**: In a standard transform model, the encoder takes an input sequence (text) and transforms it into a digital representation called an embedding. Each word in the sequence is represented by a vector in a high-dimensional space.
- **Attention mechanism**: At the heart of the Transformer is the attention mechanism. Unlike recurrent neural networks, which process data sequentially, transformers use attention to provide direct access to any position in the input sequence. This is done using "attention scores" that determine the relative importance of words to each other. The attention mechanism is often referred to as "self-attention" when applied to the same sequence.
- **Multi-Head Attention**: The transformer uses multiple attention "heads" to capture different contextual relationships. Each attention head performs a separate attention operation, then the results are concatenated and passed through a linear layer.
- **Feed-Forward Networks**: After attention, the output passes through fully connected neural networks, also known as feed-forward networks. These networks apply non-linear transformations to better capture the complex characteristics of the data.
- **Stacked layers**: A transformer consists of several layers of attention and feed-forward, stacked on top of each other. Each layer refines the representations obtained from the previous layers.

3.1.2. Pre-Training and Fine-Tuning

LLMs are first trained on large corpora of unlabeled text in a phase called pre-training. During this phase, the model learns to predict the next word in a sequence (autoregressive model) or to reconstruct a hidden sequence (auto-encoder model such as BERT). This pre-training allows the model to capture linguistic regularities and contextual knowledge. After pre-training, models can be fine-tuned to specific tasks using labeled data. For example, a model can be tuned for text classification, response generation, or machine translation tasks. This fine-tuning phase adjusts the weights of the model so that it excels at a particular task.

3.1.3. Scalability

The performance of LLMs is often related to their size, i.e., the number of parameters they contain. GPT-3, for example, has 175 billion parameters. More parameters allow the model to capture finer nuances and learn richer representations but also increase computational and memory requirements.

3.1.4. Applications

LLMs are used in applications as diverse as text generation, chatbots, machine translation, automatic summaries, sentiment analysis, solution analysis, solution correction, data formatting, technology intelligence, and the list goes on. Their ability to generate coherent, relevant text makes them extremely versatile in all sectors of society, from education to industry [22]. However, there are challenges with these models. They require huge computational and energy resources to train and deploy. What's more, they can produce biased or incorrect results because they learn from data that contains bias or misinformation. The issue of ethics and responsible use of LLMs is crucial [23], especially when these tools are used in educational settings.

4. How LLMs Are Used by Students

Unlike many North American and Asian countries, the French education system has always struggled to reform deeply, and the arrival of new technologies in the classroom has always been met with caution at best and resistance at worst. Teachers have often instilled the use of digital technology. The calculator has long been a source of tension and heated debate between those opposed to its use as an operations solver and those in favor of developing new technologies to free students from menial tasks. When it first appeared in the 1970s, the education world wondered whether it should be introduced into schools and, if so, at what level. This debate continued until the early 2000s. We experienced the same discussions, the same questions, and the same arguments when consumer computers arrived. The association "Enseignement Public et Informatique" (EPI) echoed the conclusions of the Sèvres seminar which justified the use of IT in the classroom on the grounds of complementarity of pedagogical approaches: *"Our attitude must remain welcoming to different pedagogical experiences. It seems that the introduction of IT currently takes three forms:*

- Like the teaching of a new subject (specialized sections and schools, courses for volunteers, intensive courses of a few days for all pupils at the same level).
- Like the teaching of a way of thinking within existing subjects, with each teacher finding in his or her discipline the fundamental notions of modeling, algorithms, and information.
- Like the use of a new medium, comparable to the first printed book, which helps the teacher in the repetitive part of his work" [24,25].

In the 1970s, the "58 high schools" experiment was carried out, equipped with Mitra 15 and T 1600 mini-computers. This initiative was to have a lasting impact on the future of new technologies in education. With the development of the Internet at the beginning of the 21st century, the widespread use of powerful search engines, the development of general information sites such as Wikipedia, the diversification of personal terminals (laptops, tablets, and, above all, smartphones) and, above all, the arrival of AI tools in the last three years, the learning practices of our students will be profoundly changed.

Should we ban AI, and in particular LLM, from the classroom, or should we instead support teachers and learners to use it sensibly and constructively? In a joint article, C. De la Higuera and J. Iyer try to provide some answers [9]. The authors start from the premise that it is already too late to ask the question, as AI has already penetrated all areas of education. For the learner, AI should ideally be an aid to course selection, individualized learning, an assessment, and self-assessment tool, a time manager, a personalized tutor, an alert system for students who drop out - in short, an adaptive learning system that can, in theory, eliminate failure. Of course, we'd be in the best of all worlds, where the student understands that knowledge is the key and that AI can be a tremendous support and deepener [7,27,28]. But the reality is often very different. Over-consumption of generative systems, blind faith in suggested outcomes, short-term predictions (those of graded assessments), and an appetite for solutions that minimize the cognitive load and personal workload mean that AI is no longer used as an aid, but as a substitute for learning. Why not delegate to algorithms a job that they can do much better than I can? Teaching algorithms to first-year science students (among others), I'm confronted daily with the utilitarian drift of the irrational use of AI tools.

We can identify, in a non-exhaustive way, several forms of use:

- The first, of course, is to use LLM to generate text, whether for reports or as a translation system. The student does no contextual analysis. At best, they extract a few keywords from the problem and type them into the prompt window of ChatGPT, Claude, Chatsonic or Mistral. The result is often skimmed over, and the sources are never checked. The same goes for writing algorithms or computer programs (in C, for example). Today, it's complicated to build first- or second-year computer exercises with a solution that doesn't exist on the web.
- The second way to use it, after creating content, is to correct problems. Problem-solving and debugging are important steps in learning to code. They allow you to understand the limitations and peculiarities of a language, the behavior of machines, and the need to structure developments. This can sometimes be a tedious process for programs of several hundred lines. In general, IDE (Integrated Development Environment) compilers provide little information about the location and nature of errors. For beginners, this correction task is perceived as a major obstacle and is the point in the learning process that requires the most teacher intervention. Typically, the teacher gives a few explanations about the nature of the error, a series of lines of code to check, and a few hints about the avenues to explore to correct the error. The student is often in a position of frustration, as he would prefer the teacher to "correct" his mistakes immediately. With AIG, this step disappears. Our students copy/paste their program into the LLM, build a simple prompt like "look for my mistake and suggest a correction" and the system provides a solution, sometimes with a comment on the problem, which of course the students never read.
- This work-avoidance strategy is no longer the preferred solution for students. Computer development tools now include dedicated AIs that are more efficient than generalist LLMs. A good example of this is Replit

(https://replit.com). You can work with an incredible number of templates to develop virtually any kind of application with this online tool. What's more, you can take advantage of an AI assistant. It guides you through every stage of program development, from describing the problem to fine-tuning. The system assists the student at every stage of the design—and does so quite efficiently — so that the student no longer must worry about the technical side of things (**Figure 2**). Again, the student does not have to think about how to solve the problem. Why should they? They can simply copy/paste the exercise or be guided by a selection of actions to perform. For example, you can use Replit software to brainstorm, visualise data sets or take the programmer's place by performing the task of building the program. The final result is quite impressive for beginner's code exercises.

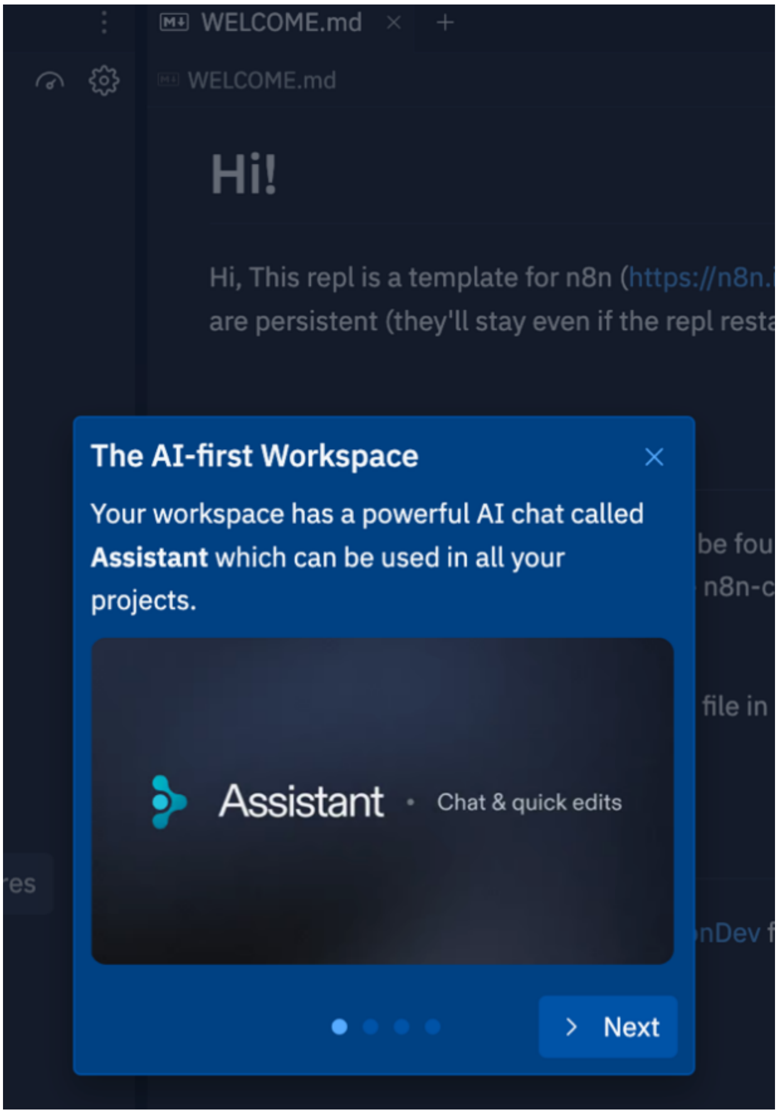

Figure 2. Replit © Help Screen.

5. Basic Learning Findings of the Study

What we are witnessing is a kind of decline in the knowledge and skills of our students. We no longer simply delegate an operation to a calculator, we no longer recover data to enrich content, and we no longer use digital technology to individualize learning or deepen knowledge. We are in a situation where a student can ignore all the pedagogical steps involved in acquiring knowledge, methods, and skills. Bloom's Taxonomy would no longer even be a coherent framework for developing learning concepts; it would no longer serve as a frame of reference for constructing the knowledge to be acquired. These assertions might seem gratuitous if they weren't backed up by pragmatic examples of results obtained with and without the help of AI. We could be optimistic and say that students regularly use these tools to minimize their gaps, complete their knowledge, and so on. But if we alternate the media used to assess this knowledge (computer, paper), we see that the performance levels are highly dependent on the medium. For 1/3 of the students, i.e., about 35 students in a class, the difference between a computerised exam and a paper exam is a factor of 3 or more. In most cases, AI is not a tool for improvement. It's a substitute tool that makes students believe they can take credit for machine results.

AI is turning our students into artificial individuals with limited knowledge, no ability to think or analyze, not to mention the inability to maintain the level of concentration required for certain types of learning. This observation is not limited to the world of education. We hear the same from industry, though not universally, when we talk to our students' work experience tutors: "Students don't know much anymore, they don't think critically, and they can't make suggestions".

6. The Impact of Using GAI on Teaching Objectives

We realized that Bloom's taxonomy, however much it had been criticized, was still a pedagogical model used to classify levels of knowledge acquisition. We saw that it contained six levels: knowledge, comprehension, application, analysis, evaluation, and creation, sometimes with slightly different names. This is partly the model on which the education system has been based for the last sixty years. Without taking a pessimistic view of tomorrow's education, we must be aware that today's students have access to tools that can give them the illusion of having acquired the expected knowledge, and that, from knowledge to creation, will be able to propose simple and effective answers to the problems posed by teachers. On the positive side, generative AI can be used to provide students with factual information and basic knowledge on a given subject [28,29]. It can generate text, images, videos, and other educational content to help students acquire knowledge. However, limiting the negative aspects to a simple ethical issue (often illustrated by the possibility of cheating in exams) would be a fundamental mistake. Generative AI could have a major impact on basic learning:

- At the level of knowledge: Generative AI can be used to provide students with factual information and background knowledge on a given topic. Admittedly, this trend didn't start with LLMs. It probably started with search engines and online encyclopedias. Why hold back information when you know So what's the difference and what's the problem? AI can very easily and quickly generate answers to a question, synthesize them, revise an explanation, and most importantly suggest a solution that will satisfy a student who doubts his or her ability to do better. Why should I know something that I can easily find via a GAI? So LLMs can free a person from the need to know. We could easily erase Bloom's first level. But what would an AI give us back for problems that have not yet been integrated into the servers, either because of timing issues such as content updates, or because the data is related to pure creativity? At best nothing, but unfortunately, this is not often the case. For example, let's use a search engine to find a recipe for Brazilian sauerkraut. You'll find the recipe for feijoada, but not a Brazilian version of the famous Alsatian dish, simply because it doesn't exist. Ask ChatGpt the same thing and no problem, a recipe for sauerkraut will be provided. Of course, this raises the question of trusting LLM answers.
- At the level of Understanding: A GAI can provide personalized explanations in real time to help understand concepts that can be complex. Even better, these explanations can be tailored to the requester's level of knowledge or age: "Explain the principle of a genetic algorithm in 30 lines to someone who hasn't done much computing". This could be an extraordinary source of help, advice, synthesis, deepening, or support. This is undoubtedly the level of Bloom's taxonomy that could be least affected by the development of digital tools. But one might ask whether understanding a problem would still be useful in the eyes of the average student? In fact, in my opinion, the answer depends entirely on the quality of the answers provided by the next level.
- At the level of Application: It is this level of learning that will be the most problematic. We can assume that the solutions to all first-level undergraduate exercises, whatever the discipline, are already on the internet and therefore archived on the LLM servers. Once our students have mastered the construction of an engineering prompt, they will find an acceptable solution to a problem through successive refinements. It takes a lot of

imagination to construct a statement that can defeat an AI system. I had fun asking ChatGPT the following question: "Can you build me a recursive C programming statement on one-dimensional integer arrays whose solution is not on the Internet? Very enthusiastic and always very polite, the system suggested an exercise to find certain sub-suites, which looked quite appealing. Knowing a bit about the Internet and AI systems, you can guess what my next question was: "Can you give me a solution to this exercise?" And then, of course, the system displayed a beautiful C program, which I copied/pasted into an IDE and which compiled and ran without a hitch. The quality of the answers provided means that problems can be solved without requiring any skills other than knowing how to ask a digital system a question. The characteristics of this hierarchical level (reinvesting methods, solving problems by mobilizing skills, etc.) may again be inhibited in the learner, who will always find it easier to ask a question. The uselessness of the understanding stage effectively neutralizes the interest of the comprehension stage.

- At the level of analysis: A non-exhaustive list of the skills required at this level of cognitive objective would include the ability to discriminate, classify, and relate facts and the structure of a statement. This requires lower levels of knowledge, understanding, and application. Generative AI could help learners develop an analytical mindset by generating complex data sets and information to help them identify trends, patterns, and relationships. It could also provide 'guidance' to help students work on their ability to analyze information. It could also generate presentations or reports by cross-referencing information from different sources. But then again, generative systems can do this better than we can, especially if we're not specialists in the field. Since I have almost no knowledge of poetry, but working in Metz city, where Paul Verlaine was born, I used ChatGPT to ask the following question: "Explain to me how Paul Verlaine's poems are different from the poets of his time". A complex analysis, given my level of knowledge of the history of poetry, the mechanics of poem construction, the different genres of poetry, and the social context of the 19th century. I can't even begin to estimate the time it would have taken me to find the information, understand the issues, put Verlaine's work into the perspective of his time, and ensure the accuracy of the results. The analysis proposed by ChatGPT and confirmed by a French teacher is coherent, justified, and would correspond to critical work done by a student in a generalist final class, and that in 3 minutes.
- At the level of Synthesis, or Evaluation: Typically, assessment aims to enable the use of ideas and to create new ones by linking knowledge from different domains. Generative AI could enable students to assess their learning by generating personalized assessments such as MCQs. This can be done very easily with just a few prompts, and it is of course possible to generate the expected answers. If we were to draw a comparison with traditional work habits, we could say that the profile of the student who would be interested in this extra work would be the one who would ask you for the explanations and corrections of previous examinations. We regularly put previous years' exams online and tell students that practice questions are available but not compulsory. The correction is automatic, and students can retake the assessment as many times as they like. We are curious to see how many students do this extra work. The percentages vary from 8% to 15%. Generally, it's not the students who are most in need who do the extra work. Generative AI opens up new possibilities for formative and summative assessment. But beware: by analyzing students' answers and providing instant feedback, digital assistants could also quickly demotivate the student, who would be set up to fail.
- On Synthesis and/or Creativity level: For a long time, we thought that this aspect of intelligence was reserved, if not for humans, then at least for living things. Creation is often unconscious. It's difficult to justify an idea. Why did Picasso go from a classical style of painting to a blue period, then to pink, then to cubism? Creativity brings into play a set of complex vague parameters that depend as much on experience, knowledge, opportunities, and techniques as on the situation. Creativity is not rational; there's no mathematical equation to define it. My AI has never said to me: "I have set myself the goal of sending a processor to the moon and bringing it back to earth in working order before the end of this decade". A computer can't come up with a new concept or idea. But it can do "like" very well. You can ask it to write a poem like Rimbaud, paint like Hopper, or play guitar like Hendrix, and it will do it well, but it will never know how to be inspired by something that doesn't exist. On the other hand, the results proposed by Generative AI are compelling. Why should our students be deprived of tools where all they have to do to generate data is to specify what is expected, such as "*I want to get a nice poster with an image of Paris hosting the Winter Olympics, with a downhill skier arriving at the foot of the Eiffel Tower*" (**Figure 3**)?

Figure 3. Image Generated by DALL.E.

Delegating creative concepts to machines creates two problems. The first one is that all GAI systems work with almost the same data and almost the same algorithms. Mathematically, all the solutions generated, however numerous they may initially be, should eventually converge on a small number of close solutions. The original idea, the one that doesn't exist, will never be proposed because the systems don't know it. The second one is that our students will gradually lose the cognitive mechanisms of reflection, ideation and innovation.

7. Conclusions

When considering the arrival of generative AI in the classroom, we can envisage two contrasting scenarios for the impact of these assistants on the cognitive development of our students. The first optimistic view suggests that the inevitable integration of generative AI into education offers significant opportunities to enhance and personalize learning. If we were to try to construct the typical profile of a student who would take full advantage of generative AI, we'd say he or she should be:

Intellectual curiosity: Being curious allows you to ask pertinent questions and explore different subjects in depth.

Critical thinking: Analyze and evaluate LLM responses for accuracy and relevance.

Clear and precise: Formulate clear and precise questions to obtain useful answers.

An analytical mind: Knowing how to interpret and synthesize information to integrate it into your academic work.

A spirit of research: Use a GAI as a complement to other sources of information, not as a sole source.

Ethics and academic integrity: Use LLMs ethically, avoiding plagiarism and correctly citing sources.

Autonomy: Being able to work independently using the tool to support autonomous learning.

Creativity: using GAIs to generate innovative ideas and solutions.

Problem-solving skills: Use answers to solve complex problems.

Admittedly, this would be an ideal student. He already has the maturity and intellectual honesty to understand the challenges and benefits of working with generative tools. He would certainly not be in a competitive system where grades and place determine whether he continues or graduates. Unfortunately, most of the cohort entering the first year of a bachelor's degree has a significantly different profile. And that would be a pessimistic view of the use of GAIs. How can we resist the urge to substitute the use of a generative tool for personal work, especially when the latter is perceived, rightly or wrongly, as superior to one's abilities? As with the optimistic version, we could list the negative effects of using Generative IA:

Over-dependence: Students may become too dependent on LLMs for their academic work, reducing their ability to think critically and independently.

Plagiarism and academic integrity: The use of LLMs can facilitate plagiarism, as students may submit AI-generated content without proper citation.

Reduced research skills: The use of LLMs can reduce students' skills in traditional research and source evaluation.

Superficiality of knowledge: LLM answers can sometimes lack depth, leading to a superficial understanding of the subjects studied.

Loss of creativity: Overuse of LLMs can limit students' ability to develop their own creative ideas and solutions.

Lack of engagement: Students may be less motivated to actively engage in the learning process if they can get quick and easy answers from LLMs.

Writing skills: The reliance on LLMs can hinder the development of students' writing and communication skills.

Development of interpersonal skills: Interaction with LLMs does not replace human interaction, which is essential for the development of interpersonal skills.

Inequality of access: Not all students have equal access to the technologies needed to use LLMs, which can exacerbate inequalities.

Ethics and responsibility: Students may not always understand the ethical implications of using LLMs, particularly in terms of bias and fairness.

The integration of LLMs into the classroom offers significant opportunities but also carries significant risks. The pedagogical concepts on which teachers rely are certainly challenged by generative systems. Classification, as proposed by Bloom, is supposed to design learning objectives, assessments, and pedagogical activities that promote deep understanding and practical application of knowledge, but wouldn't it become obsolete if each of these skills could be recalled when needed by writing a simple prompt?

Educators, policymakers, and technology developers must work together to mitigate these dangers by putting in place appropriate governance measures and raising awareness of the potential negative impacts so that artificial intelligence does not just create real dummies.

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Data Availability Statement

No data are presented in this study. The analysis of the experimental results will be published at a later date.

Conflicts of Interest

The author declares no conflict of interest.

References

1. Bloom, B. S.; Engelhart, M. D.; Furst, E. J.; et al. *Taxonomy of Educational Objectives: The Classification of Educational Goals, Handbook I: Cognitive Domain*; Longmans, Green: New York, NY, USA, 1956.
2. Anderson, L. W.; Krathwohl, D. R.; Bloom, B. S. *A Taxonomy for Learning, Teaching, and Assessing: A Revision of Bloom's Taxonomy of Educational Objectives*; Allyn & Bacon: Boston, MA, USA, 2001.
3. Krathwohl, D. R. A revision of Bloom's taxonomy: An overview. *Theory Pract.* **2002**, *41*, 212–218.
4. Jain, J.; Samuel, M. Bloom meets Gen AI: Reconceptualising bloom's taxonomy in the era of co-piloted learning. **2025**, Not Peer-Reviewed. Preprints.org. [CrossRef]
5. Krutka, D. G.; Heath, M. K.; Willet, K. B. S. Foregrounding technoethics: Toward critical perspectives in technology and teacher education. *J. Technol. Teach. Educ.* **2019**, *27*, 555–574.
6. Lee, M.; Winzenried, A. *The Use of Instructional Technology in Schools: Lessons to Be Learned*; Acer Press: Camberwell, VIC, Australia, 2009.
7. Groff, J. *Personalized Learning: The State of the Field and Future Directions*; Center for Curriculum Redesign: Boston, MA, USA, 2017. Available online: https://dam-prod.media.mit.edu/x/2017/04/26/PersonalizedLearning_CCR_April2017.pdf (accessed on 25 April 2025).
8. Zawacki-Richter, O.; Marín, V. I.; Bond, M.; et al. Systematic review of research on artificial intelligence applications in higher education–where are the educators? *Int. J. Educ. Technol. High. Educ.* **2021**, *18*, 1–28. [CrossRef]
9. De la Higuera, C.; Iyer, J. *AI For Teachers: An Open Book*; Pressbooks. Available online: https://web.unican.es/buc/Documents/Formacion/AI-for-Teachers-an-Open-Textbook.pdf (accessed on 25 April 2025).
10. Krathwohl, D. R.; Bloom, B. S.; Masia, B. B. *Taxonomy of Educational Objectives, The Classification of Educational Goals, Handbook II: Affective Domain*; David McKay: New York, NY, USA, 1973.
11. Gardner, H. *Les Intelligences Multiples. Changing Schools: Taking Different Forms of Intelligence Into Account* [in French]; Retz: Paris, France, 1996.
12. Gardner, H. *Frames of Mind: The Theory of Multiple Intelligences*; Fontana Press: Waukegan, IL, USA, 1993.
13. Biggs, J. B.; Collis, K. F. *Evaluating the Quality of Learning: The SOLO Taxonomy*; Academic Press: New York, NY, USA, 1982.
14. Gagné, R. M. *The Conditions of Learning*; Holt, Rinehart and Winston: New York, NY, USA, 1965.
15. Gagné, R. M. Contributions of learning to human development. *Psychol. Rev.* **1968**, *75*, 177–191. [CrossRef]
16. Weizenbaum, J. ELIZA–a computer program for the study of natural language communication between man and machine. *Commun. ACM* **1966**, *9*, 36–45.
17. Rabiner, L. R. A tutorial on hidden Markov models and selected applications in speech recognition. *Proc. IEEE* **1989**, *77*, 257–286.
18. Hochreiter, S.; Schmidhuber, J. Long short-term memory. *Neural Comput.* **1997**, *9*, 1735–1780.
19. Vaswani, A.; Shazeer, N.; Parmar, N.; et al. Attention is all you need. In Proceedings of the 31st Conference on Neural Information Processing Systems (NIPS 2017), Long Beach, CA, USA, December 4–9, 2017.
20. Radford, A.; Wu, J.; Child, R.; et al. Language models are unsupervised multitask learners. *OpenAI Blog* **2019**, *1*, 8.
21. Brown, T. B.; Mann, B.; Ryder, N.; et al. Language models are few-shot learners. *Adv. Neural Inf. Process. Syst.* **2020**, *33*, 1877–1901.
22. Wolf, T.; Debut, L.; Sanh, V.; et al. Transformers: State-of-the-art natural language processing. In Proceedings of the 2020 Conference on Empirical Methods in Natural Language Processing: System Demonstrations, Online, November 16–20, 2020; pp 38–45. [CrossRef]
23. Bender, E. M.; Gebru, T.; McMillan-Major, A.; et al. On the dangers of stochastic parrots: Can language models be too big? In Proceedings of the 2021 ACM Conference on Fairness, Accountability, and Transparency, Virtual, March 3–10, 2021; pp 610–623.
24. Enseignement Public & Informatique (EPI). Public Education & Information Technology (EPI). Editorial from EPI Bulletin No. 1 [in French]. *Rev. EPI* [in French] **2001**, *104*, 201–204. Available online: https://edutice.archives-ouvertes.fr/edutice-00000893/document (accessed on 23 April 2025).
25. Baudé, J. The Sèvres seminar (March 1970) [in French]. *Bull. Soc. Inform. Fr.* [in French] **2017**, *11*, 115–127. Available online: https://1024.socinfo.fr/2017/09/1024_11_2017_115.pdf (accessed on 23 April 2025).
26. Zaphir, L.; Hansen, D. The trouble with Bloom's taxonomy in an age of AI. *Times Higher Education*. Available online: https://www.timeshighereducation.com/campus/trouble-blooms-taxonomy-age-ai (accessed on 23 April 2025).
27. Niu, W.; Zhang, W.; Zhang, C.; et al. The role of artificial intelligence autonomy in higher education: A uses

and gratification perspective. *Sustainability* **2024**, *16*, 1276. [CrossRef]
28. Faraon, M.; Granlund, V.; Rönkkö, K. Artificial intelligence practices in higher education using Bloom's digital taxonomy. In Proceedings of the 2023 5th International Workshop on Artificial Intelligence and Education (WAIE), Tokyo, Japan, September 28–30, 2023.
29. Ifenthaler, D.; Majumdar, R.; Gorissen, P.; et al. Artificial intelligence in education: Implications for policy-makers, researchers, and practitioners. *Tech Know Learn.* **2024**, *29*, 1693–1710. [CrossRef]