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**1AC**

## 1AC---Scholarship

**The advantage is SCHOLARSHIP.**

**GAI is key to research.**

**Brown 24** [Monika; Freelancer in data visualization; 3-21-2024; "How Generative AI Can Improve Scientific Experiments", University of Chicago Booth School of Business; https://www.chicagobooth.edu/review/how-generative-ai-can-improve-scientific-experiments; DOA: 2-12-2025] sumzom

**Artificial intelligence** is rapidly changing jobs and industries, causing no small amount of consternation as it does. But on the bright side, it has the potential to greatly aid economists by **streamlining experiments’** design and implementation and leveraging behavioral insights, suggests research by University of California at Santa Barbara’s Gary Charness, Chicago Booth principal researcher Brian Jabarian, and University of Chicago’s John A. List.

Recent advances in generative AI, mainly through large language models, have sparked considerable interest. For one example, after OpenAI launched LLM-based ChatGPT, its valuation exploded, competitors rushed to keep up, and Microsoft kicked in $10 billion. Across the world, people are scrambling to understand how LLMs will transform jobs, the labor market, and various companies and sectors.

Science, as many researchers have noted, is not immune. And as Charness, Jabarian, and List explain, LLMs can help revolutionize how it is practiced. Addressing economists in particular, they write that LLMs could be harnessed to scale up experiments, make findings more accessible, and foster a culture of critical thinking of evidence-based analysis. LLMs could be used to improve nearly **every step** of an **experiment**, they explain—and they propose specific approaches for doing so. “All these offered directions require experimental benchmarking before becoming established scientific policies,” qualifies Jabarian.

They group their recommendations into three categories: the design phase of an experiment, the implementation phase, and the analysis phase. Design involves crafting and **coding** an experiment, and here, they write, LLMs offer a groundbreaking approach to **literature review**, **hypothesis generation**, and **experimental setup**. LLMs could be used to **analyze** extensive **data** sets, identify **gaps in knowledge**, and help generate **research ideas**. AI could speed up the brainstorming phase while ensuring that research hypotheses are well-grounded.

Once a research question or hypothesis is in hand, LLMs could recommend a suitable experimental design, be it an economic game, market simulation, or something else. Drawing on knowledge learned from their training data, they could guide whether an experiment should be conducted in the lab or the field (or both). AI could help determine the optimal sample size for study and calculate the minimum number of participants needed to achieve statistically significant results—balancing the need for robustness with practical considerations such as cost and time limitations.

In the implementation phase of an experiment, the real-time capabilities of LLMs become particularly useful, the researchers write. By functioning as interactive chatbots, LLMs could provide **immediate support** to participants, **clarify instructions**, **answer questions**, and ensure **compliance** with the **experimental protocol**. They would produce a better experience for participants while also safeguarding the integrity of and monitoring an experiment. If a participant were to **misunderstand instructions**, become **less engaged**, or even **cheat**, LLMs could **detect that** and take steps to **address it**—all while reducing the workload for human researchers and minimizing the potential for **errors**.

And LLMs would significantly expand the scope and depth of data interpretation in the analysis phase, according to the research. Through state-of-the-art natural language processing techniques, they could analyze **qualitative data** such as participant feedback or chat logs, and extract insights that traditional statistical methods might **miss**. They could organize and clean data **efficiently**, which not only **speeds up** the pre-analysis process but allows researchers to focus on **interpreting results** and drawing conclusions. And LLMs could be used to conduct statistical tests, generate visualizations, and identify patterns or correlations.

Ultimately, generative AI opens up new avenues for exploration and discovery, the researchers write. But while outlining these and other advantages, Charness, Jabarian, and List acknowledge risks to using LLMs in experiments, “including concerns about intellectual property (IP), digital privacy issues, user deception, scientific fraud by fabricating data or strategies to hide data manipulation, hallucinations,” and more. Reliance on LLMs could result in less creative research questions, they posit, as standardization in prompts and other processes “could, in principle, create research drones” and “lead to lost opportunities for new wisdom, thought, hypotheses, and scholarship needed in the face of every new societal challenge.”

But the advantages of using LLMs, they conclude, **outweigh** these drawbacks—and the scientific community should adopt a structured approach that amplifies the **benefits** and reduces the risks. Creating such a **framework** would hopefully, they write, “foster a culture of policy and industry experimentation at scale.”

**Downsides are self-corrected.**

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Ever-growing scientific advances and data present a significant challenge: a ‘burden’ of knowledge that leaves researchers struggling to keep up with the expanding scientific literature. By contrast, the explosion of knowledge and data is fuelling machine intelligence. The rapid progress in **generative AI** (see box 1 for a non-technical primer) in the past few years, especially in large language models (LLMs), is a **game-changer** [1,2]. It is well suited to alleviate the **knowledge ‘burden’** and has the potential to revolutionize **scientific research**. To facilitate the adoption of this new technique and foster discussions and empirical research on the changing landscape of scientific research in the era of generative AI, here I provide a how-to guide for using LLMs in academic settings and offer new perspectives on their implications as informed by epistemology and philosophy of science.

Box 1. Generative AI, large language models and ChatGPT/Bard.

Generative AI trains machine learning (ML) models on a dataset of examples to generate new examples similar to those in the training set, including text, images and music. This generative ability distinguishes it from predictive AI, which trains models to **predict outcomes** on new, unseen data, such as in image classification and speech recognition. Although generative AI dates back to the 1950s, the breakthrough came only recently, thanks to the availability of massive amounts of data and the development of deep learning algorithms (‘deep’ refers to the use of multiple layers in artificial neural networks). These algorithms afford the creation of **large language models** (LLMs) to be trained on vast amounts of diverse text data.

Many state-of-the-art LLMs use a type of deep learning algorithm called transformers as their backbone. Introduced in 2017, the transformer architecture is a type of deep neural network architecture that uses self-attention mechanisms to better process sequential data such as text. Self-attention allows the network to calculate the attention weights between every pair of input elements, effectively allowing the network to weigh the importance of each input element with respect to all other elements. Thus, it allows the network to dynamically focus on different parts of the input sequence and capture long-range dependencies in the data. This mechanism enables it to understand and interpret language in a way that is similar to humans.

One of the most powerful LLMs is Generative Pre-trained Transformer 3 (GPT-3), introduced in 2020 by OpenAI in San Francisco, California. GPT-3 has been trained on a massive amount of text data, allowing it to generate human-like text and excel at challenging natural language processing (NLP) tasks. Recently in November 2022, a derivative of GPT-3 called ChatGPT was launched. It has fine-tuned GPT-3 using reinforcement learning from human feedback (RLHF) in a smaller dataset specifically for conversational tasks, making it both conversational and computationally efficient. GPT-3 was updated to GPT-4 and released to the public on 14 March 2023. Another powerful transformer-based LLM is PaLM (Pathways Language Model), developed by Google AI. PaLM has been finetuned to support the chatbot, Bard.

To understand and harness the capacity and potential of generative AI, I will illustrate its capabilities using the popular chatbot ChatGPT. ChatGPT reached 100 million users within just two months of its launch on 30 November 2022. A similar chatbot is Bard, which was launched by Google on 21 March 2023 (see table 1 for a list of other tools). In what follows, I will first identify and elaborate on three features of LLMs, as exemplified by ChatGPT, that make them unprecedentedly apt to augment, if not transform, research life: intelligent, versatile and collaborative. I do so by incorporating specific, practical examples commonly encountered in biomedical and behavioural research. As LLMs are rapidly evolving, I also offer a living resource online, complete with documents that provide tips on crafting effective prompts, examples of usage and relevant links (https://osf.io/8vpwu/).

<<TABLE 1 OMITTED>>

Next, I will critically discuss the limitations of LLMs and, importantly, their ethical and responsible use, as well as implications for equality and education—a debate still in flux. Specifically, I argue that while **guidelines** for using AI such as ChatGPT in academic research are urgently **needed**, policing its usage in terms of plagiarism or AI-content detection is likely of **limited use**. More fundamentally, if AI-created content is deemed valuable based on peer review, there is no reason to reject such content—the identity of the originator of that content is irrelevant from an epistemic point of view. As long as the use of AI is transparently disclosed, there is no need to limit the scope or nature of the assistance it can offer. If, however, the content produced by AI is not original or valuable but still passes peer review, then the problem lies not with AI but with structural issues in the peer review system—AI merely exposes its **weaknesses** and calls for **concerted efforts** to improve it. Concerning implications for equality, I contend that generative AI may foster equality for some but exacerbate disparities for others, based on considerations at the individual, group, and national levels. With regard to education, I advocate for the importance of engaging with LLMs and developing critical thinking and analytical skills in students. Given the early nature of generative AI in scientific research, empirical work is scarce, and the views expressed here aim to stimulate further efforts in addressing these important issues.

2. Three features of generative AI that make it valuable for researchers

2.1. Intelligent

AI is created to perform tasks that typically require **human intelligence**, including understanding language. According to multiple benchmarks—ranging from Advanced Placement (AP) exams to the Uniform Bar Exam—it is increasingly capable of performing language tasks at a level that matches or **surpasses** average **human performance** [3]. Indeed, LLMs such as ChatGPT go beyond generating language to show some form of behaviours that seem to resemble general ‘intelligence’, including problem-solving and reasoning [4].

Formal tests corroborate these observations. For example, in medical question answering, ChatGPT not only achieved accuracy higher than the 60% threshold on the National Board of Medical Examiners (NBME) Free Step 1 dataset—comparable to a third-year medical student—but was able to provide reasoning and informational context [5]. As another example, consider its ability to generate medical-research abstracts based on just the title and journal of the original papers. Not only was there no plagiarism detected, but also human reviewers correctly recognized just 68% of the generated abstracts and wrongly flagged 14% of the original abstracts as generated [6]. These results are remarkable given that they were tested using ChatGPT out of the box. In other words, when the pre-trained model is fine-tuned with a dataset of examples from the relevant domains, the results will be enhanced. Further, as the underlying model (GPT-3.5) is continually being improved (e.g. updated to GPT-4 on 14 March 2023), the performance of ChatGPT is expected to also improve, as demonstrated in medical competency [7].

Whether such performance and behaviour constitute cognitive abilities and can be construed as intelligence of humankind is debated [8]. Indeed, human intelligence is a latent construct that does not yield itself to a straightforward measure in non-human animals and machines, not least because traditional intelligence tests such as Intelligence Quotient (IQ) are anthropocentric—designed specifically for humans. Even within human populations, IQ tests need to be significantly altered for testing in children and people with disabilities. Thus, to better understand the nature of AI and measure its progress in obtaining intelligence, much research is needed to define intelligence and measure it in a way that is comparable and fair across machines and mankind [9].

Given the controversy, the term intelligence will be used here to refer to artificial intelligence, regardless of whether that might be considered true human intelligence or not. Indeed, for practical purposes—that is, from an end user's perspective—such debates are mostly moot so long as AI is able to get the job done. To appreciate the intelligence of AI, perhaps the most straightforward way is to have a conversation with ChatGPT (for a practical guide to its efficient use, see box 2). ChatGPT is strikingly human-like: it ‘understands’ text input and responds to it like a well-learned person—and in some ways, perhaps better than most people. The implications are likely to be profound, as the cost of intelligence has never been so low. This makes LLMs such as ChatGPT incredibly empowering for organizations and individuals.

Box 2. A practical guide to the efficient use of ChatGPT/Bard.

ChatGPT can be accessed through a web interface. To get started, go to the official webpage (https://chat.openai.com) and sign up for an OpenAI account (phone verification is required). Once logged in, you will see its interface, as shown above, where you will find example prompts to ask the chatbot and its capabilities and limitations. Interact with the chatbot by typing your prompt in the blank input bar (bottom) or initiating a new chat (top left).

To use it more efficiently, familiarize yourself with three key features. First, each prompt in your chat history has an edit button when you hover over it (on the right), where you can edit your previous prompt. After your edit, the chatbot will provide a new response accordingly. This is useful when your initial attempt does not yield the response you want. Second, you can provide feedback on the response (thumb up and thumb down icons, on the right) and you can ask it to regenerate responses (bottom)—which you can toggle to compare and find the most desirable one. Third, you may want to start a new chat for each project, as ChatGPT takes into consideration the chat history of each conversation.

Getting the desired results may require some thought. That is, feed it the right prompts (see six tips for writing effective prompts in the online supplemental materials: https://osf.io/8vpwu/). LLMs tend to make assumptions about user intent based on the prompt given, rather than asking clarification questions. To enhance accuracy, it is important to provide it with sufficient contextual information [10]. In general, prompts should be clear and concise. You can provide very specific instructions and offer feedback and new directions as follow-ups throughout the conversation. For example, you may ask it to explain a statistical concept by typing: ‘Explain Cook's distance’. Suppose you find the response a bit dense. You can follow up by typing: ‘Can you explain it like I am five?’ As another example, you can feed it with your writing and ask it to make it more concise: ‘Please rewrite it to be more concise’. But if you find the rewrite a bit non-sophisticated, you can follow up with a prompt like: ‘Please make it more sophisticated for an educated audience’. You can keep fine-tuning it to your desire. However, if you have a clear goal, using an elaborate, specific prompt will work best. In fact, you can enlist ChatGPT to help improve the prompt (e.g. ‘Please evaluate each prompt I present and provide a rating on a scale of 1 to 5, based on its clarity and level of engagement. Kindly provide constructive feedback on how I can improve each prompt if necessary. Should the rating for a prompt be 4 or above, proceed to answer it; otherwise, create a new prompt that meets the desired criteria’).

ChatGPT is helpful for many things, from helping you learn, code, analyse and write to assisting with your teaching, mental needs and job applications. Ultimately, to get the most out of its capabilities, be creative and imaginative. Say you have written an emotional email. Before you send it, you can enlist ChatGPT to check its tone, using the following prompt: ‘Acting as an editor, please make recommendations on how to improve the email below using the principles and concepts of Nonviolent Communication (NVC). For each edit, please provide the rationale and some examples’. Indeed, you can ask ChatGPT to act as a simulated patient, therapist, coach, advisor, tutor, professor or interviewer—the possibilities are endless. Or consider your next job application. You can request ChatGPT to help craft a customized cover letter for the job, using a prompt like: ‘Please write a cover letter for the job description below using my CV that follows’.

Example screenshots of using R and Adobe Illustrator, tips for writing effective prompts, and a living resource are provided online (https://osf.io/8vpwu/). This guide also applies to the chatbot, Bard, which is highly similar to ChatGPT except for some minor differences (e.g. the ‘[r]egenerate response’ function in ChatGPT is replaced by the ‘[v]iew other drafts’ function in Bard).

For knowledge workers, it enables us to be more productive and efficient—doing more with less. A list of tips, examples and resources is provided online (https://osf.io/8vpwu/). For example, ChatGPT can provide explanations and help us learn a new domain more efficiently (e.g. ‘Act as an R instructor and teach me the basics'), write and debug codes faster (e.g. ‘Write R code to do a one-way ANOVA based on the following data’), assist with writing (e.g. ‘Rewrite the following paragraph to be more concise’) and more. By automating aspects of the research process and improving research efficiency, ChatGPT helps to accelerate the pace of scientific discovery.

From the perspective of philosophy of science, AI also has the potential to **uniquely complement** and enhance human intelligence in facilitating **scientific inquiry** and **discovery**. For one, by analysing and synthesizing vast amounts of data from different fields, LLMs may help to discover connections between seemingly **disparate fields**—connections that might not be immediately apparent to **human researchers**. For another, whereas human researchers are **inevitably influenced** by personal values and preferences, social norms and cultures, and historical assumptions and biases [11], LLMs do not have emotions, consciousness or personal **motivations**. Indeed, by analysing vast and diverse amounts of data with the same algorithmic process, LLMs have broader perspectives and **greater consistency** than individual researchers, thus reducing the **risk** of cognitive bias, from confirmation bias to the availability heuristic. Moreover, although biases do exist in LLMs due to the training data and algorithms—a limitation discussed later—these biases are not **identical** to human biases and can help to counteract or reduce certain predispositions in scientific practices, potentially improving the **reliability** and **objectivity** of scientific inquiry [‘strong objectivity’; 12].

2.2. Versatile

As alluded to before, what makes **generative AI** such as ChatGPT special is that it excels not just in one domain but across **many domains**, thanks to the diverse training text data. ChatGPT has been trained to understand and generate cohesive text across a broad spectrum of subjects, from general knowledge to specific areas such as **science** and mathematics. It is proficient in a wide range of human languages (English, Spanish, French, German, Italian, etc.) and computer programming languages (Python, JavaScript, Java, C++, R, etc.). This versatility makes it useful in multiple capacities, such as a coach, research assistant and co-writer.

Consider the many tasks that researchers perform every day. In administrative roles, writing and editing documents and emails can benefit from ChatGPT. In teaching, generating questions and grading them, creating discussion points and questions, editing syllabuses and handouts—these are some common tasks that can also use help from ChatGPT. In research, too, practically all processes—other than those involving physical interactions—can enlist ChatGPT. Indeed, formal evaluations in finance research show that ChatGPT can significantly assist with idea generation, data identification and more. Incorporating private data and domain expertise can further improve the quality of the output [13].

For example, ChatGPT can help with familiarizing oneself with new topics (e.g. ‘What is generative AI’), **summarizing** (e.g. ‘Summarize the key issues mentioned below in a table, using two columns: ‘Ethical issue’ and ‘Key question’’), **coding** (e.g. ‘The following code has errors. Can you advise how to fix it’), **brainstorming** (e.g. ‘Write five titles based on the following keywords’), providing feedback (e.g. ‘Act as a journal reviewer and provide feedback on the abstract below’) and more.

2.3. Collaborative

ChatGPT is also special for its **conversational capability**, thanks to a method called reinforcement learning from human feedback (box 1). This capability makes it an excellent **collaborator**, able to listen and update its responses based on **user feedback**. To illustrate, suppose we want to improve our writing. We can start with the prompt: ‘Act as a copy editor, revise the text below and explain your edits’. If we don't like a particular expression in the revision, we can follow up with a new request: ‘Can you make ‘…’ more elegant?’ Indeed, we can ask ChatGPT to give the writing some personality, revise it for an academic audience, make it more persuasive or assertive, in the style of Hemingway, and so on. From proofreading to editing and rewriting, the possibilities are **endless**.

The utility of intelligent, versatile, always-on collaboration afforded by ChatGPT cannot be overstated. It offers a great channel to bounce ideas off of. It also helps to alleviate common drudgery and mental block—making research more fun. For example, regular expressions (regex or regexp) are a powerful tool commonly used in text analysis to define patterns for strings—thus enabling matching, extracting, and substituting patterns—but they can be complicated and error-prone. ChatGPT makes it much easier to use regex by helping researchers understand the syntax and usage (e.g. ‘How to replace all occurrences of Ph.D. with PhD in R using regex?’), and then construct or refine a regex (e.g. ‘Test the regex on a sample text and return the matched substrings’). Similarly, consider a common mental block: writer's block. ChatGPT helps by brainstorming and collaborating with us, starting the first step that ultimately paves the way for a thousand-mile journey to publication (e.g. ‘Give me five ideas to begin an article on ‘how AI may help researchers’’).

3. Limitations of generative AI

As with any other tool, generative AI has limitations. These limitations are rooted in the principles and techniques that make it so powerful in the first place (box 1). Specifically, LLMs such as ChatGPT are language models trained on massive data. When they respond to queries and engage in conversation, they do not understand the content in the same way humans do, but rather make predictions about text based on patterns learned from training. They ostensibly write like an educated human—a great achievement—but they are not. This will become plainly clear once we interact with them in a deep manner (e.g. they can contradict themselves at times, and they do not have a strong grasp of context). The important point, however, is to use them as powerful tools rather than relying on them.

In the context of research aid—such as for a research project or for lecturing on a topic—a major limitation of LLMs is that they may fabricate facts, creating confident-sounding statements and legitimate-looking citations that are false (hallucination). Thus, as with any other source of information (e.g. Wikipedia), it is important to critically evaluate and verify AI responses, particularly when reliability is critical [14]. An important next step might lie in developing methods to quantify and signal the epistemic uncertainty and potential limitations of AI-generated results.

Still another limitation has to do with the training data for LLMs. These data are not—and cannot be—truly neutral or objective, but rather laden with assumptions and biases, ranging from political and ideological to cultural [12,15]. From the perspective of standpoint epistemology, such biases and assumptions are not inherently problematic. To the extent that knowledge is socially situated—different people have different experiences and perspectives that shape their understanding of the world—biases and assumptions can be understood as reflective of specific standpoints (i.e. perspectives) of the people who generated and compiled the data.

Yet, the challenge is that the standpoints represented in the training data may not be evenly distributed or representative of all perspectives. Indeed, the issue of underrepresentation in knowledge production has been widely documented, including the underrepresentation of certain racial, ethnic, gender, political and geographical groups as participants and researchers in medical and scientific research [16,17]. Lack of diversity in the research process contributes to prejudices, stifles epistemological plurality, and limits the range of topics and questions being pursued [11]. In turn, biases and limitations in the data may be picked up—or even amplified—in LLMs. For example, when the training data predominantly reflect the views and experiences of certain groups (e.g. people from Western, educated, industrialized, rich and democratic societies), then the LLMs trained on these data will inevitably reflect these biases. This uneven representation can lead to a reinforcement of dominant perspectives and marginalization of others, creating a potential for bias in the outputs of these models.

There are additional limitations in using AI/LLMs to aid teaching and administrative tasks. In the realm of teaching, one potential use of AI is grading [18]. While such an application might seem promising in terms of efficiency, establishing a system that grades objectively, reliably and fairly presents significant challenges. To ensure fairness and accuracy, the AI’s grading algorithms would need to be based on clear, comprehensive rubrics—a non-trivial task in itself. Even then, potential biases in the AI’s interpretation of student work could lead to discrepancies in grading. Furthermore, nuances of student creativity and originality, which are often the hallmarks of exceptional work, might be overlooked or misinterpreted by an AI grader. Therefore, human supervision and verification are necessary safeguards in the grading process, potentially reducing the time and labour-saving benefits of the AI.

In the administration domain, AI is useful for drafting emails and similar tasks. While AI can be used to streamline the process and improve efficiency, it can also backfire in sensitive situations, when human touch is what matters most—something that cannot be replaced by AI. One case that underscores this limitation is a recent incident at Vanderbilt University, where two deans used ChatGPT to draft an email to students about a mass shooting at Michigan State University. Their use of AI in this sensitive situation led to their suspension, illustrating the potential pitfalls of over-reliance on AI for sensitive administrative tasks. Thus, striking a balance between leveraging AI's efficiency and maintaining the human touch that is often essential in academic settings will be an ongoing challenge in the implementation of these technologies.

4. Implications of generative AI: ethical use, equality and education

4.1. Ethical and responsible use

The power of generative AI such as ChatGPT raises many thorny questions regarding its ethical use, from plagiarism, image manipulation, authorship and copyright to fake research (table 2). It is one thing to ask it to act as an editor to correct language issues in our own writing, but quite another to ask it to write an entire paragraph and then copy it [2]. The former is similar to the services offered by other writing tools and university writing centres, while the latter is widely regarded as plain plagiarism. However, the boundary between acceptable help and too much help is not always clear-cut. When we feed ChatGPT with our own text and ask it to rewrite it, is that too much help to be considered ethical? Does the answer depend on the length of the text—and if so, how can we determine the proper boundary? The same questions apply to text-to-image AI (e.g. DALL·E 2, Midjourney, Stable Diffusion). Is it okay to use AI-generated images in the paper, or would that be considered plagiarism? And in the cases where AI offers ‘too much’ help, can it be listed as a co-author? Fundamentally, who has the right to claim copyright over AI-generated content (text, images, etc.): the prompt creator, the AI, the AI developer or the owners of the training data?

<<TABLE 2 OMITTED>>

These questions are important for the community to consider and address. Currently, publishers and journals are divided in their policy and stance on some of the questions. For example, Springer Nature does not allow LLM tools to be listed as authors, and requires researchers to document their use in the paper [19]. On the other hand, Science family journals not only ban AI tools as authors, but also prohibit the use of AI-produced content (text, images, figures, graphics) in the paper [20]. Although such swift decisions are understandable, going forward it is important to engage the whole scientific community to reach a more consistent and informed consensus. For example, banning AI tools as authors because of their inability to take responsibility flies in the face of the long-standing practice of posthumous authorship [1].

The more practical issue is that it may not even be feasible to detect AI-generated content with sufficient accuracy to be useful. Compared with typical AI-generated content, human-generated content generally—but not always—has higher burstiness, mixing longer or more complex sentences with shorter ones, and with higher perplexity, using words that are less expected [21]. However, some human writers do write with low burstiness and perplexity, posing a problem of false positives for algorithms. Moreover, LLMs can be instructed to write content with higher burstiness and perplexity, creating a problem of false negatives for algorithms. On top of that, given that LLMs are constantly evolving and improving, it is reasonable to assume that their ability to evade detection may do so as well. Thus, although algorithms for detecting AI content may be useful to compare different groups of writing, they are unlikely to be able to ‘convict' any individual writing. Banning the use of AI-generated content may prove challenging to implement.

Fundamentally, if AI-created content is valuable, there is no reason to reject such content. From an epistemic point of view, we should not treat a finding differently just based on the status of the author, whether it is a Nobel-prize winner or a junior academic member. The identity of the author is irrelevant. The same applies to AI: if AI has **valuable**, original content, there seems no **epistemic** reason to **devaluate** it just because it is created by AI. The real question is the vetting of its value—which rests on the human author and reviewers. Thus, a more **pragmatic** approach to AI in **academic publishing** is to encourage or mandate its **transparent use** [22] rather than banning it outright or even limiting it. From this perspective, there is no need to limit the amount or kind of help from AI—no concept of too much help from AI—as long as it is transparently reported.

Perhaps a more urgent issue with AI concerns its potentially serious threat to scientific integrity: the inevitable exponential rise of AI-generated, fraudulent papers submitted to scientific journals—some of which will pass peer review and become part of the scientific literature. Paper mills, which are already notorious for creating and selling fake research with fraudulent data and images, will become an even bigger threat when equipped with the unprecedented power of AI [10]. However, the negative disruptions brought about by AI, as with the advent of any other powerful tool in history, are to be expected. Indeed, more generally, if content that is not valuable or simply **fake** can pass **peer review**, whether it is from AI or not, the problem has more to do with the **peer review system**. The potential negative impact is not a cause to forbid or limit the use of AI, but a call to step up our efforts in implementing **better practices** in scientific **review** and publishing.

Such practices may involve the implementation of rigorous and **open peer review** (e.g. published peer review exchanges), collaborative review (e.g. discussions among reviewers and the action editor before making an editorial decision) and open science practices (e.g. open data and materials). These practices serve to deter **fraudulent submissions**, as through open review, the review process is subject to **scrutiny** by the wider **scientific community**; they also enhance the probability of detecting fraudulent content, as the accessibility of data and materials **simplifies** the process for others to validate the results. For these practices to be most effective, researchers need to be aware of the potential for AI tools to be used to generate fraudulent content, as well as to be alert to potential signs of such fraudulent content. Thus, **education** and awareness are **vital**. In addition, **AI-based tools** may be developed to **detect** patterns indicative of **data fabrication** or falsification, as well as to identify inconsistencies or errors in data analysis. Together, these strategies can help mitigate the **negative impact** of AI on knowledge production and improve the accuracy of the scientific record more generally.

4.2. Impacts on equity

Having discussed the strengths, limitations and ethical use of generative AI, a natural question arises concerning its implications for equity. Perhaps paradoxically, the availability of powerful, versatile AI tools can promote equality for some while amplifying disparities for others. On the one hand, a main contributor to global disparities in scientific research is language; for example, most mainstream journals are in English, bestowing a natural advantage on native English researchers [16,17]. LLMs can help level the linguistic playing field by offering a language boost for non-native English researchers through copy editing and other writing assistance (e.g. ‘Act as a copy editor, proofread the following text for an academic journal, and highlight the changes at the end’). Thus, researchers previously disadvantaged in the English language can now compete on a more equal footing.

**The new generation of early career researchers won’t misuse AI.**

**Herman 24** [Eti; CIBER Research, Newbury, Berkshire, UK; 9-4-2024; "The impact of AI on the post‐pandemic generation of early career researchers: What we know or can predict from the published literature", Wiley Online Library, https://onlinelibrary.wiley.com/doi/full/10.1002/leap.1623; DOA: 2-13-2025] sumzom + mac

\*ECR - Early Career Researcher

However, in the specific case of harnessing AI, they are in a different position, as this time any groundbreaking attempt they may come up with will focus on the technological components of doing research. Thus, their efforts will not directly affect the scholarly standards and principles, widely held to be inherent to the academic reward system, even if repercussions of changes to the former can hardly be expected to leave the latter untouched. With the principal barrier to adopting novel ways of conducting, disseminating, and evaluating scholarship thus seemingly rendered less relevant when it comes to the adoption AI, ECRs are **well-positioned to introduce change**. After all, today's millennials are digital natives (Prenksy, 2001a,b), who, having been born into an internet-centred and media-rich world, are ‘tech-savvy’ by inclination and keen, confident and competent users of digital technologies. Thus, the ECRs among them, too, often have the most **up-to-date expertise on technology** and **methodologies in their research fields** and boast the **digital skills that drive today's globalized research** (Powell, 2021). Indeed, having repeatedly proven their tendency to be early adopters of novel technologies that can assist in scholarly practices, as their enthusiastic embracing of social media for the purpose demonstrates (Clark et al., 2024; Nicholas, Jamali, et al., 2020; Nicholas, Watkinson, et al., 2020), they could be in the forefront of the utilization of AI in research work, too.

In fact, even at this early stage there is empirical evidence indicating that they are likely to see the opportunities afforded by the adoption of AI. Thus, an exploratory study into the use of ChatGPT in education, research and healthcare indicates that **junior academics** are not only **more interested in using** the **technology** than senior faculty, having more positive views, interest, and acceptability beliefs in using it, but more of them had already tried it, too (Hosseini et al., 2023). Undoubtedly, their patterns of AI-use indicate a potentially favourable attitude to the novel opportunities thus afforded to them: in the Nature postdoc survey (Nordling, 2023a), 31% of employed respondents reported using chatbots, with 43% of the users doing so on a weekly basis and 17% daily, even if for most (67%) AI brought along no change in their day-to-day work or career plans. As Bianchini, Müller & Pelletier (Bianchini et al., 2023) find in their exploration of the factors that can influence the decision of scientists to adopt AI, **ECRs** can and already do **play a pivotal role** in the process. This, as they contend, for two main reasons. First, young researchers, well-versed as they are with AI techniques and tools, have the necessary skills required for AI-driven scientific work. Second, they can bring new perspectives and insights to their more experienced colleagues, showing them ways of conducting and communicating research that differ from their usual ways of going about their scholarly pursuits.

Thus, ECRs are indeed likely to play a part in the harnessing of AI-powered techniques for **scholarly purposes**. Plainly, though, the extent of their contribution will be contingent upon the benefits and challenges they will encounter along the way, and the way their idiosyncratic circumstances, as novice researchers, will be affected. This review of the literature on the AI-associated, conceivable and/or already-felt improvements and impediments to the processes and practices of research, will focus on the potential consequences these will have for ECRs.

AI-DRIVEN POTENTIAL CHANGES: THE ECR ANGLE

Producing new knowledge

With research achievements widely seen as synonymous with scholarly success, indeed, as the sine qua non of all scholarly rewards—employment, tenure, promotions, resources, job mobility, awards/prizes, and monetary remuneration—the crucial importance accorded to the pursuing, creating, and disseminating knowledge reigns on among today's academics. However, it is quantitative productivity, rather than qualitative productivity, which still holds sway over scholars, and in fact, resonates just as powerfully with the present generation of researchers as it did with their predecessors (Blankstein, 2022; Blankstein & Wolff-Eisenberg, 2019; Desrochers et al., 2018; Herman, 2018; Herman & Nicholas, 2019; Moosa, 2018; Nicholas, Herman, et al., 2015). This situation is inevitably of a prime concern for junior researchers, yet to establish themselves in academia (Jamali et al., 2023; Nicholas et al., 2017; Nicholas, Herman, et al., 2020; Nicholas, Jamali, et al., 2020), especially considering that they have been compelled to fight harder than past generations for a decreasing share of the academic pie. Thus, any means of enhancing their productivity would appeal to them.

Certainly, as we shall learn, AI-assisted research, affording as it does more efficient ways of working, does indeed seem to fit the bill. It is with good reason that these tools have even been described as research co-pilots (Conroy, 2023), co-researchers (Ansari et al., 2023), co-authors (Zielinski et al., 2023), research assistants (Hutson, 2022), writing assistants (Imran & Almusharraf, 2023), even members of a hybrid innovation team (Dwivedi et al., 2023). However, the benefits of AI for producing new contributions to the extant body of knowledge seem to come at a price. As Van Dis et al., (Van Dis et al., 2023) point out, voicing oft-heard concerns, while AI might very well accelerate the innovation process and bring about a productivity boost, it could also degrade the quality and transparency of research, producing poor-quality papers with text that may look convincing, but often contains inaccuracies, bias, and plagiarism. It is, unsurprisingly, a prospect that gives rise to apprehension in the scholarly community, as the findings of the Nature survey of 1,600 researchers prove: the most disturbing problems of AI were seen to be its potential to spread misinformation, to make plagiarism easier to do and harder to detect, to introduce mistakes and bias into research texts, and to make it easier to fabricate or falsify research (Van Noorden & Perkel, 2023).

It might be thought that ECRs, driven to publish to survive and prosper as they are, may more readily succumb to the temptations of **using AI indiscriminately** to accelerate their research productivity. However, **judging from the findings of the Harbingers project** about their attitude to publishing in predatory journals—the epitome of **straying from the straight and narrow in scholarly publishing**—it is **highly unlikely** that they would do so (Nicholas, Herman, Abrizah, et al., 2023; Nicholas, Rodríguez-Bravo, Boukacem-Zeghmouri, et al., 2023). With publishing in predatory journals not even a feature of their research world, both because it is seen as **going against their ‘scholarly code of honour’** and because **institutional and communal dragooning ensures that they rarely think it is a possibility**, it is hard to imagine that they will be more susceptible to overlooking the negative aspects of AI use. This situation needs to be kept in mind throughout the exploration of the capabilities of AI-based tools to impact on each stage of the generic workflow of the knowledge producing process (Garvey, 1975), which follows: formulating research questions and hypotheses, anchoring the research problem in the extant literature, collecting and analysing data and interpreting the findings.

Formulating research questions and hypotheses

In the initial stages of research **AI tools can help brainstorm** emerging ideas. Used as a sounding board, these tools can facilitate an iterative process that begins with the researcher's entering into the system key questions, concepts, and arguments as prompts, seeking to elicit sentences, paragraphs or whole texts that can serve as the basis for formulating the problem to be explored and assessing its quality (Ansari et al., 2023; Susarla et al., 2023). In this way AI-powered tools, just like colleagues, can **help discover a scientifically significant research topic by providing insights**, **criticism**, and **feedback**, which is a bonus for more isolated scientists (Dwivedi et al., 2023; ERC—European Research Council, 2023). It is not very surprising to find then that scholars already use generative AI for brainstorming new ideas and generating new research hypotheses: for example, in an early Nature survey, brainstorming research ideas was ranked the most common, with 27% of the 486 respondents indicating they had tried it (Owens, 2023). In another Nature survey, that of 1,600 researchers around the world, brainstorming was cited among the benefits and positive impacts of AI, coming third in popularity among the uses listed (Van Noorden & Perkel, 2023).

This capability of AI-based platforms to serve as a partner in the pathfinding processes preceding a research project must be particularly welcome to novice researchers, even if in the Nature postdoc survey (Nordling, 2023a) it was not mentioned among the ways AI is already used. Still, **ECRs**, relatively inexperienced in identifying a researchable topic as they usually are, and yet to **form** close enough **connections with other scholars** to allow for **free exchanging of ideas**, are likely to need assistance in doing so. After all, this is one of the reasons why, as part and parcel of the process of completing the crucially important transition from dependent to fully independent researcher, they rely on the help of their mentors (Castellanos et al., 2022; Laudel & Gläser, 2008). It has long been so, but the pandemic brought things to a head, for the pressures senior researchers battled had a knock-on impact on their ECR colleagues, who, in result, were failing to receive the support they needed (Watchorn et al., 2020; Woolston, 2020). So much so, that an important, possibly permanent impact of the pandemic, at least in the United Kingdom, was found to be the realization that mentoring had to be taken more seriously (Nicholas et al., 2022b). Meanwhile, perhaps AI can help provide some of the assistance they need in this area.

Only some, though, for with all that the ability of AI to assist in finding a research topic it is hardly a cure-all. Indeed, here we encounter for the first time the reservation that will be a recurring theme in the forthcoming exploration of the ways that generative AI can be deployed for research purposes: the fact that the quality of generative AI models, which largely depends on the quality of the data that these tools are trained on, is not always up to par (Fui-Hoon Nah et al., 2023; Van Dis et al., 2023). In the case of using AI for problem formulation, as Susarla et al. (2023) point out, it is the currency of the data (or, to put it more accurately, the lack thereof) which is the problem. This means that the suggestions for research questions, raised by AI tools, are likely to be the ones findable in the established corpus of knowledge, rather than forward-looking, state-of-the-art ones at the forefront of the research on a topic. Thus, while tools such as ChatGPT can highlight areas of interest and suggest potential topics for exploration, the identification of genuine research gaps and the generation of novel hypotheses require human judgement and analysis (Rice et al., 2024). True enough, but as Dwivedi et al. (2023) contend, **even if AI delivers less original and valuable ideas** than humans, **it can still play the role of coach** and facilitate better understanding of a problem and the solution space.

Anchoring the research problem in the extant literature

Another important aspect of producing new knowledge that can benefit from the utilization of AI-powered tools is the anchoring of a research problem in previously obtained understandings via an analytic review of the pertinent literature. As shown in a number of articles, reviewed in AlZaabi et al. (2023), AI tools are well-suited to **searching, screening, retrieving and analysing large literature databases** to **generate narrative text** and can, therefore, **significantly accelerate** and **render more efficient** the process of **assembling the literature base for a research project**. Lending evidence-based support to this notion are the findings of a survey, conducted by the European Research Council—ERC (ERC—European Research Council, 2023) among its more than 1,000 grantees, which focused on their present use of AI and their views on future developments: 85% thought that AI can efficiently handle repetitive or labour-intensive tasks, such as conducting literature reviews. By the same token, in the Nature survey of 1,600 researchers the assistance that can be had from AI in preparing literature reviews was ranked as popular, coming in sixth out of 14 uses mentioned (Van Noorden & Perkel, 2023).

However, as Ngwenyama and Rowe (2024) suggest, with all that AI can turn experts in literature review into super experts, researchers need to exercise great caution when utilizing AI tools in the process of reviewing the literature. With good reason, too, for one of the main concerns, invariably noted in the discussions of the uses to which AI tools can be put, is the above-noted possibility of the inadequate quality of their output. Take just one example, emerging from the European Research Council (ERC) survey: 62% of the respondents expressed concern that generative AI could spread false information or inaccurate scientific knowledge. The most talked-about worry is the so-called hallucinations—texts that give the impression of being fluent and natural, despite being unfaithful and nonsensical (Ji et al., 2023), but the literature lists quite a few additional problems. These include outputs that can be difficult to understand; outputs that may contain difficult-to-discover mistakes; outputs that, having been manipulated, may not be authentic; outputs that, having been elicited through inadequately engineered prompts, are erroneous or misleading; outputs that lack citations, without which it is difficult to judge the credibility and trustworthiness of the ideas presented (Fui-Hoon Nah et al., 2023; Susarla et al., 2023). No wonder then that **researchers, utilizing AI-techniques** in their research undertakings, are **strongly urged** to use their **traditional competencies to critically select, analyze and interpret the review** of the literature achieved in this way (Ngwenyama & Rowe, 2024; Tiunova & Muñoz, 2023).

This situation poses a particularly great risk to novice scholars, who are often tasked, as the veritable ‘workhorses’ of research, with the time-consuming task of reviewing the literature (Jamali et al., 2020; Nicholas et al., 2017). As they are constantly in a rush, not in the least because they are spending twice as much time on research as their older counterparts to prove themselves and win the race for one of the scarce tenure-track academic positions (Baker, 2020a), they might be tempted to cut corners by accepting unquestioningly AI tools as legitimate reviewers of scientific knowledge. In fact, although in the Nature survey of postdocs only about a third used AI in their work, finding/summarizing the literature was one of the more popular usages, with 29% of the respondents opting for it. Not a huge percentage (yet?), but users are already conscious of the problems that opting for the practice can bring about: according to the postdocs interviewed for the article reporting the results of the survey, AI tools are great for **taking the drudgery out of academic work**, but using them without appropriate training wastes a lot of time (Nordling, 2023a).

Collecting data, analyzing it, and interpreting the findings

Another area where AI can aid in the production of new knowledge is **data generation, collection, and analysis**, noted appreciatively in quite a few of the articles reviewed by AlZaabi et al. (2023). So much so, that in social psychology research, for example, this capability of AI tools has been deemed a significant leap forward in advancing knowledge in the field (Salah et al., 2023). This, as Susarla et al., 2023 explain, is because AI-based tools can support both the assembling of data sets and the identifying of deep patterns in the data, so that manual, time-consuming tasks, such as matching variables across archival sources, are automated. Beyond that, AI can even be applied to explore text data to surface patterns, thereby serving as an aid for researchers seeking to identify and evaluate alternative approaches to solving problems.

However, these advantages, as both Salah et al. (2023) and Susarla et al. (2023) emphasize, need to be used with caution, with the researcher carefully verifying the quality of the results, for AI is not a substitute for human reasoning and cognition. Here again, the warning to avoid over-reliance on AI is traceable to the quality of the data that the tool has been trained on. Thus, biases in the database, such as internet-based replications of existing social biases—sexism, racism, and ageism—or too much focus on developed countries, which have the financial capabilities to maintain a dataset, or on over-represented languages, most notably English, can lead to biases in the results produced (Hosseini et al., 2023; Susarla et al., 2023; Tiunova & Muñoz, 2023).

Nevertheless, AI can provide valuable support for collecting and analyzing data in a more timely and efficient manner, and researchers seem to be well-aware of the benefits of taking advantage of the opportunity. Thus, in the aforementioned Nature survey of 1,600 participants, AI's capability to provide faster ways to process data were ranked first among the positive impacts reported, with two-thirds of the respondents saying so. The automation of data acquisition and the possibility to process new kinds of data also ranked quite highly, fourth and fifth, respectively (Van Noorden & Perkel, 2023). In fact, according to the results of the ERC grantees poll, AI tools are already seen as an essential tool for data analysis, with their employment for the purpose very much disciplinary-specific. Thus, in the life sciences AI is used for analyzing large volumes of imaging data and to find complex patterns and/or to generate simulations; in the physical sciences and engineering for analyzing, classifying, and forecasting physical phenomena, for example, weather patterns, air pollution, volcano deformation, and earthquakes; and in the social sciences and humanities, for analysis of data sets of texts, from image segmentation, text mining, up to conceptual and linguistic models (ERC—European Research Council, 2023). Hardly surprisingly, young researchers, looking to using their time more effectively, have come to recognize the advantages of using AI for data analysis, as exemplified by the relatively high percentage—56%—of chatbots users among postdocs, who reported in the Nature survey to having employed AI to generate, edit and troubleshoot code (Nordling, 2023a,b).

Disseminating and publishing research findings

Scholars see to it that their work is adequately described for peers to critique and use and for future generations to build upon in their own work, for, as the old saying goes, the scholar whose work is known only to themselves is forgotten, in fact, has never been ‘known’ (Glicksman, 1990). The composing and writing up of the findings of a research study are an important part of a researcher's pursuits, conscientiously undertaken despite its time-consuming nature. The next step undertaken then in the dissemination process of research results is the crucially important one of choosing the right outlet for publication.

Producing a research manuscript

Arguably, one of the more consensually recognized and much-appreciated benefits of leveraging AI for research purposes is its capability to support, indeed expedite manuscript development (AlZaabi et al., 2023; Duarte, 2023; Dwivedi et al., 2023; Imran & Almusharraf, 2023), which can bring about the productivity boost that scholars require. ChatGPT-style tools, which, true to their characterization as ‘generative’ not only recognize patterns, but create new data based on those patterns, can produce an entire research paper. However, as attempts to give the possibility a try have proven beyond doubt, the resulting manuscript leaves a lot to be desired: while the papers might be clearly written, they contain fake citations and inaccurate information (Conroy, 2023).

Here again, as Dwivedi et al. (2023) suggest, with AI building its sentences and discourse from data traces, it is the breadth and depth of the training materials which is to be blamed for circumscribing the capabilities of AI-based tools. Thus, as they go on to say, AI is in fact, as Bender et al. (2021) famously dubbed it, a ‘stochastic parrot’, which does not offer a conversation, does not understand, does not communicate and does not really produce knowledge. Luckily, awareness of the limitations of AI, inter alia for producing research papers, seems widespread. For example, from among the 1,600 researchers participating in the Nature survey on AI and science, 68% worried about proliferating misinformation and 66% were concerned about mistakes or inaccuracies brought into scholarly outputs (Van Noorden & Perkel, 2023).

It seems the prevalent view then, that AI cannot be relied on to write a paper in its entirety, which is one of the reasons why publishers have been updating their policies, refusing to accept texts uniquely generated by ChatGPT (and similar tools) as original pieces of work or to allow for chatbots to be an author. Other reasons for the latter are the inability of these tools to agree to be a co-author and the fact that they cannot be held accountable for the work published (Duarte, 2023; Dwivedi et al., 2023; Yatoo & Habib, 2023). Certainly, as a paper which explored the potential for an AI-based system to be a co-author on an academic paper found, while the paper produced showed promise in fulfilling the criteria for co-authorship, as recommended by the International Committee of Medical Journal Editors (ICMJE), the semantics in the criteria implied that personhood and a legal status as human was necessary for authorship, disqualifying any AI system from authorship (Osmanovic-Thunström & Steingrimsson, 2023).

What AI can do, though, is produce content that can serve as the first draft of a manuscript, to be critically assessed by human experts, which, of course, is still a great improvement over starting from scratch (Dwivedi et al., 2023). However, representing a more subdued take on the role that AI can play in writing, Susarla et al. (2023) regard the option of getting AI-powered tools to generate even draft sections as ceding control of the knowledge-creation process, and, as such, a mistake. Instead, they suggest that AI's assistance be limited to what it does best, that is, the assessing of the structure of arguments and/or the quality of writing in a manuscript to enhance its readability.

Be it as it may, there can be little doubt that the real forte of AI-powered tools is the improvement of writing style and the expedition of proofreading—a host of articles, reviewed by AlZaabi et al. (2023), bear testimony to the prevalence of this view. It is hardly surprising that it would be so for all researchers, but especially for the less experienced among them, for, as Borger et al. (2023) suggest, poorly written articles can hinder effective communication, impede the dissemination of scientific findings within the scholarly community and beyond, and erect barriers to conveying to funders the significance of a proposed research. Indeed, in the recent Nature survey of 1,600 researchers the greatest benefit accorded to AI tools was their ability to improve the grammar and style of research papers (Van Noorden & Perkel, 2023). By the same token, in the Nature survey of postdocs, for whom publications can make or break their careers, 63% of the respondents used AI for refining text, the most common use reported (Nordling, 2023a).

This is more so where non-native English speakers are concerned, for, as Amano et al. (2023) find in a survey of 900 researchers, non-native English speakers, especially early in their careers, spend more effort than their native English speaker counterparts on writing papers and preparing presentations in English. Obviously, then, AI-powered tools, capable as they are of improving the language and coherence of papers, can level the playing field for non-native speakers, in general, and ECRs included (AlZaabi et al., 2023; Yatoo & Habib, 2023). In fact, in the Nature survey of 1,600 researchers not only was the clearest benefit of AI tools found to be their ability to improve the grammar and style of research papers, but it was thought to be particularly advantageous for scholars whose first language is not English (Van Noorden & Perkel, 2023). Similarly, in the ERC poll, 75% of the grant recipients felt that AI would reduce language barriers in research (ERC—European Research Council, 2023). The problem is, to reiterate a point already made, that chatbots, while ‘fantastically talented’, are prone to producing ‘cogent waffle’, that is, grammatically accurate combinations of chunks of text that do not really say anything useful and may also contain misinformation (Vincent, 2022).

Choosing the ‘right’ outlet for publication

Once the manuscript is completed, the next step in the dissemination process of research results is the choosing of the ‘right’ outlet for publication. As the publishing venue is a key indicator of the extent to which a scholarly achievement is seen as representing a significant, and therefore rewardable contribution to science, the significance of choosing well where a research paper is to be published cannot be overstated (Niles et al., 2020; Pontika et al., 2022; Teixeira da Silva, 2021b). However, selecting the best fit-for-purpose publishing venue is a complex decision, for varying multiple factors need to be taken into consideration and weighted according to the idiosyncratic circumstances of the individual investigator (Forrester et al., 2017). The prestige of the publishing venue, its standards of peer review, the appropriateness to the target audience, and, in the case of journals, their impact factor and indexation in WoS and/or Scopus, just to name the most frequently noted factors, all come into consideration (Nicholas et al., 2017; Nicholas, Herman, Clark, et al., 2022).

Thus, the capability of the available AI-based journal recommendation tools to identify appropriate journals with relatively high accuracy, as Kousha and Thelwall (2024) conclude from their review of several pertinent studies, can be of great help for researchers in the decision-making process. This, incidentally, is not the case when it comes to identifying predatory journals, for the available AI-driven software that claims to effectively discern ‘normal’ from ‘suspected predatory’ journals, currently gives an apparently high false positive output (Kendall & Teixeira da Silva, 2024).

Here again, novice researchers, relatively less experienced, and yet less knowledgeable about the options on offer in their field are even more likely than their senior colleagues to benefit from harnessing AI-powered systems when they set out to choose an appropriate publishing outlet. True, they often work as part of a research team: for example, in a survey of ECRs, which explored their authorship practices, 82.7% of the 1,598 respondents said they did. However, with all that this situation certainly indicates that the choice of a publishing outlet is not solely their responsibility, they also reported that they had some influence in the publishing decisions of their team, with 41% saying that they had big influence, and another 48% saying they had some influence (Jamali et al., 2020).

Evaluating research

Another—and a particularly challenging—component of the scholarly communications system, where AI is seen as capable of making a contribution, is the peer review procedure. Seen as indispensable for safeguarding the quality, novelty, reliability, soundness, theoretical and empirical validity, and potential impact of new knowledge produced (Eve et al., 2021; Nicholas, Watkinson, et al., 2015; Tennant & Ross-Hellauer, 2020), peer review has nevertheless been found to be wanting, manifesting as it does a host of characteristic limitations (for a review, see Nicholas, Herman, Abrizah, et al., 2023). With the pandemic exacerbating or at least shedding new light on the manifold problems inherent to the system in its present configuration (Horbach, 2021; Nicholas, Herman, Boukacem-Zeghmouri, et al., 2023; Nicholas, Herman, Clark, et al., 2023), the need to find novel ways and means of conducting peer review comes even more to the fore. A full exploration of the role that AI can potentially play in doing so is beyond the scope of this paper, but the emergent developments in this area that pertain to the reviewing practices of the individual scholar are very relevant indeed.

Reviewing a paper submitted for publication

As Kankanhalli (2024) suggests, with the number of submissions to peer-reviewed journals growing relentlessly because of the all-pervasive publish-or-perish atmosphere in academe, and the burgeoning numbers of active researchers, a strain has been placed on peer reviewers. It is where AI has the potential to improve the efficacy of the peer-review process and thereby save the time of reviewers. Indeed, some progress has already been made in achieving the goal, since experiments have come up with positive correlations between human and automated decisions. Thus, for example, Checco et al. (2021) found in their investigation of the possibility a strong correlation between word distribution, readability and formatting scores, and the outcome of the review process, so that their AI-assisted system was often able to successfully predict the peer-review outcome reached because of human reviewers' recommendations.

However, as Kousha and Thelwall (2024) suggest, the positive correlations between peer-review judgements and machine learning, found so far, do not indicate impending progress, as an AI system would achieve a positive correlation by rejecting papers with obvious grammatical or referencing errors. In fact, as they conclude from their extensive review of the state of the art in AI-assisted peer review, no current system challenges human reviewing. Tellingly, the American Association for the Advancement of Science—which publishes Science—allows for some use of AI tools during manuscript preparation, but still bans their use for peer reviewing, in order to make reviewers devote their full attention to the manuscript being assessed (Prillaman, 2024). Similarly, Springer Nature asks peer reviewers not to upload manuscripts into generative AI tools, noting that these still have ‘considerable limitations’ (Chawla, 2024). Indeed, Kankanhalli (2024), Susarla et al. (2023), and Van Dis et al. (2023), inter alia, all warn against using AI tools indiscriminately for reviewing, calling for human, expert-driven fact-checking and verification processes, always.

Researchers have their finger on the pulse of AI-associated developments, for the available empiric evidence indicates very little use of chatbots and/or similar tools to ease the burden of reviewing duties. Thus, for example, in the Nature survey on AI and research, reviewing manuscripts is ranked among the least popular uses of AI-assisted tools, and as the least popular of the benefits accorded to these tools (Van Noorden & Perkel, 2023). However, change might be in the air, as the results of a preprint indicate (Chawla, 2024). The study, which identified buzzword adjectives that could be hallmarks of AI-written text in peer review reports, suggests that up to 17% of the reviews had been substantially modified by chatbots, either to construct reviews from scratch or to edit and improve first drafts. Anticipating developments along these lines, only around half of the participants in the ERC poll thought that by 2030 it was ‘unlikely’ or ‘highly unlikely’ for AI to autonomously conduct the entire peer review process (ERC—European Research Council, 2023).

As to ECRs—there is obviously a sense of trepidation among them when it comes to harnessing AI to the peer-review procedure, as none of the postdocs said in the Nature survey that they used chatbots for the purpose (Nordling, 2023a). This, despite their being experienced in reviewing: belying their junior status, 58% and 78%, respectively, of the interviewees in Harbingers-1 and Harbingers-2 have undertaken peer reviews of other people's papers (Nicholas, Herman, Rodríguez-Bravo, et al., 2023). Not much of a surprise here, though. As noted, while they may be happy to carry through the new attitudes and technical facility characteristic of digital natives into their research, as junior scientists they cannot take the risk of relying on novel technologies being developed until they can be sure that these will not have any adverse effects on their own—or their peers'—scholarly careers. AI-assisted peer review is certainly a case in point: with the publication of research achievements hinging on peer review, the refereeing process assumes a pivotal role in shaping the fate of academics.

CONCLUSIONS

This exploration of the impact of AI-based tools and systems on the scholarly community, while based, as far as possible on the actual happenings on the ground, considers critical forecasts of future developments, too, as empirical studies on the topic are yet few and far between. Thus, our appreciations of the situation are more in the nature of educated analyses, which, however, are founded on the wide-ranging and in-depth empiric explorations of ECRs' communication practices and attitudes of the Harbingers project. Thus, it is clearly yet to be comprehensively and robustly established how AI is being incorporated into research, and what role ECRs might play in the process underway, which is what we aim to do in Harbingers-3. We are thus certainly at a unique place in time to observe developments as these happen, indeed, as these coalesce to form a multi-faceted portrayal of the AI-associated scholarly advances made, and to establish how the people on the frontline—the researchers, in general, and the ECRs, among them, in particular—are being impacted.

The main conclusion to emerge from this review of what is already known and/or predicted to be the consequences of the introduction of AI is, as Susarla et al. (2023) propose, that the potential for AI in revolutionizing research lies in the ability to harness its strengths, address its limitations, and forge a path forward for its prudent use. However, our analysis of the studies, editorials, opinion pieces and deliberations of the topic enables us to take a step forward to suggest further that ECRs can play an important role in shouldering this task. Certainly, in each of the already extant and potentially forthcoming AI-associated changes to the processes and practices of research that have been identified, ECRs are a cohort likely to experiment with AI and reflect on its benefits and challenges.

As the Harbingers project has shown, ECRs boast generational characteristics that render them well-suited for shedding light on the ways in which the current system can incorporate AI in its practices. As digital natives, and true to their reputation as millennials, whose defining generational characteristics are openness to change and flexibility, they are well-placed to identify where and in what ways AI can enhance, or, perhaps alternatively endanger traditional ways and means of conducting scholarly work. As dedicated researchers, and prolific authors, ECRs, despite their relatively lowly status in academe, possess the solid disciplinary knowledge basis that renders them capable of judging the value and authenticity of AI-based contributions. True, they are cautious when it comes to harbouring ‘revolutionary’ thoughts, for fear of endangering their careers, but when it comes to AI-based novel ways of conducting, disseminating and evaluating scholarship, they are on safer ground—it is the technological components of doing research, rather than the traditional scholarly standards and principles, which are likely to be affected.

Beyond that, ECRs are the ones who clearly stand to gain from adopting novel AI-enabled systems and techniques, so it is in their best interest to reflect on the improvements and impediments resulting from the move. Among these, the most appealing for novice researchers must be the benefits of enhancing their productivity, the key to all scholarly rewards, inclusive of career advancement. Thus, the help of AI tools in brainstorming emerging ideas towards formulating research questions and hypotheses is likely to be appreciated by this less well-connected group of researchers, as must be the efficient ways in which AI can help in handling repetitive or labour-intensive tasks, and even the assembling of data sets and the identifying of patterns in the data. It stands to reason, of course, for we are talking here of ECRs—a particularly overworked and often rushed cohort of researchers. For the same reasons, leveraging AI to expedite the disseminating and publishing of research findings is surely another bonus of noteworthy attraction for ECRs, especially when it comes to producing a research manuscript, but even in choosing the ‘right’ outlet for publication or getting assistance in improving the efficacy of the peer review process.

However, ECRs, along with the whole scholarly community, will need to exercise caution when it comes to the temptations of AI-afforded questionable behaviours, but then, they have amply proven their ability to stand up to challenges. Their successful emergence from the pandemic bears testimony to this, as does their resistance to predatory journals. There is every reason to believe that ECRs will be capable of identifying and taking a responsible attitude to the problems that AI introduces, such as its making fraud easier to commit or its entrenching bias or discrimination in data.

Finally, it is too soon to come to definite conclusions as to the impact of AI on today's generation of ECRs. We already have gained first intimations of their initial reactions to the changes AI introduces to research and can make educated guesses as to how down the way they might react to the already extant developments and those said to further unfold in the future. However, it is only via a methodical exploration of their attitudes and practices, as exemplified by the Harbingers-3 study, already underway, that we will be able to establish how they view and how they use AI-assisted systems and technologies in their research.

**Universities are unique to create innovations, economic growth, and to model globally.**

**CRU 12** [Committee on Research Universities; Board on Higher Education and Workforce; Policy and Global Affairs; National Research Council; It; 2012, "Read "Research Universities and the Future of America: Ten Breakthrough Actions Vital to Our Nation's Prosperity and Security" at NAP.edu", National Academies Press, https://nap.nationalacademies.org/read/13396/chapter/5#41] mac

America’s research universities, through education and basic research, have emerged as a major asset—some would say **the most potent asset**—for the United States as the nation seeks economic **growth** and national goals. This did not happen by accident; it is the result of prescient and deliberate federal and state policies that have powerfully shaped these institutions.

CREATING THE AMERICAN RESEARCH UNIVERSITY

Before World War II, the federal government and research universities played only a small role in scientific research and its dissemination, with a couple of notable exceptions in agricultural research and extension and early efforts in public health. Scientific research and technological change were carried out by individual researchers and inventors and by industry, which either capitalized on the innovations of others or developed their own industrial laboratories to incorporate science and engineering directly into product development.

The structure and power of the nation’s science and engineering enterprise changed dramatically during World War II. Critical to the war effort, a federal-university partnership created by President Franklin Roosevelt and led by Vannevar Bush led to significant uses of scientific and technological breakthroughs in the war—including radar, the proximity fuse, penicillin, DDT, the computer, jet propulsion, and the atomic bomb—and in industry.1 As Vannevar Bush wrote in the 1945 report Science: The Endless Frontier:

We all know how much the new drug, penicillin, has meant to our grievously wounded men on the grim battlefronts of this war—the countless lives it has saved—the incalculable suffering which its use has prevented. Science and the great practical genius of this nation made this achievement possible.

Some of us know the vital role which radar has played in bringing the United Nations to victory over Nazi Germany and in driving the Japanese steadily back from their island bastions. Again it was painstaking scientific research over many years that made radar possible.

What we often forget are the millions of pay envelopes on a peacetime Saturday night which are filled because new products and new industries have provided jobs for countless Americans. Science made that possible, too.2

With the value of the partnership clearly demonstrated during wartime, this set up a model for the postwar future.

The model was harnessed to both civilian and military goals in the post–World War II era. Bush proposed, in Science: The Endless Frontier, a new partnership to achieve economic growth, national security, and the public health. Through this partnership, basic research would be increasingly funded by the federal government and largely concentrated in the nation’s research universities.

This partnership gradually emerged over the next 15 years, encompassing a range of federal agencies and an increasing number of public and private research universities. The federal government science establishment expanded through the creation of the National Science Foundation (NSF), the expansion of the National Institutes of Health, the establishment of the National Aeronautics and Space Administration and the “Space Race,” the research and development programs of the Departments of Defense, Energy, and Commerce (National Institute for Standards and Technology and the National Oceanic and Atmospheric Administration). At the same time, university research expanded. For example, from 1958 to 1968, academic research and development (R&D) grew by 417 percent; academic research expenditures, by 587 percent; federally funded academic R&D, by 618 percent; and federally funded basic research, by 702 percent. At the same time, the G.I. Bill led to the vast expansion of the university enterprise in a way that reinforced the growth of research. Consequently, as Clark Kerr asserts, “At the end of World War II, perhaps six American universities could be called research universities, in the sense that research was the dominant faculty activity…. By the early 1960s, there were about 20 research universities and they received half of all federal research and development funds going to higher education. In the year 2000, there were at least 100, and many more were aspiring to this status.”3

AN ECOSYSTEM OF DIVERSE INSTITUTIONS

This federal-university partnership has led to the creation of a large, diverse ecosystem of public and private research universities in which each institution plays critical local, regional, and national roles. An expansive view of the ecosystem would identify perhaps as many as 200 or more institutions that either award research doctorates or have more than $35 million in annual R&D expenditures. One observer has argued that about half of these, or 125 institutions, generate **most of the new knowledge from research**. This more limited set of institutions include about 60 institutions that are large, comprehensive research universities and rank among the top 100 universities globally. There are another 60 or so that educate undergraduate and graduate students and conduct research, but have a more limited set of fields in which they seek to excel in either doctoral education or research.4 The ecosystem also includes our national laboratories that provide a unique capacity for large-scale, sustained research projects that would be inappropriate for universities, such as the deep space missions of the Jet Propulsion Laboratory or the Advanced Light Source at Lawrence Berkeley National Laboratory. Yet it is important to note that most of these large laboratory projects involved both university faculty and graduate students as key players.

For our purposes, research universities are those that share certain values and characteristics and participate in an “ecosystem” of research universities in which institutions interact—through cooperation and competition (see Box 3-1). Many of these values and characteristics distinguish

<<FIGURE OMITTED>>

American research universities from their counterparts around the world and the ecosystem they participate in may also be distinguished from its counterparts. The traditional European model of higher education emphasizes centralized planning, state control, state funding, little com-petition, and a focus on research and advanced training. In the American ecosystem, by contrast, there is significant diversity among research universities in size, geography, and missions. The ecosystem is characterized by decentralization, pluralism (public and private institutions), diverse funding sources (endowment, federal, state, tuition), high levels of competition, and a hybrid model that includes undergraduate education, graduate study, and research “in the same place, done by the same people, frequently at the same time.”5 These distinctions have made our ecosystem **extremely productive**. Indeed, the success of the U.S. system has prompted others to move toward our system, for example, the ongoing debates about the higher education sector in the United Kingdom.

The U.S. ecosystem and its productivity, argues Jonathan Cole, is importantly defined by “unprecedented, vast” federal funding for science and technology research. Hugh Graham and Nancy Diamond note that higher education grew substantially in the post–World War II era because of growing economic prosperity, the baby boom, and revolution in federal science policy. The last of these more specifically drove the expansion of the nation’s research universities. And, as a consequence, “American universities, not widely respected in the international community of scholars and scientists prior to World War II, subsequently won preeminence among the world’s leading institutions.”6

The U.S. ecosystem and its productivity, argue Graham and Diamond, also are importantly defined by a large, competitive, national market for faculty in which state funding has also played a critical role. This market emerged among a small set of prominent institutions between 1900 and 1925. In this system, faculty careers were defined by upward mobility through lateral movement that made the curriculum vitae all important, a primary attachment to profession rather than institution, and research productivity. In this environment, public research universities could only provide salaries competitive with those of private research universities through economies of scale and state appropriations.7

QUALITY AND IMPACT

Measuring the direct contribution of universities, through this federal-state-university partnership, on the economy and society is a complex task,8 yet a series of indicators reveal a pattern of quality and impact.

<<FIGURE OMITTED>>

First, in indicators of relative success and quality as measured against their peers globally, American research universities and the work they do are ranked individually and collectively as the best in the world:9

• Nobel Prizes: Before World War I, Nobel Prizes were largely awarded to Europeans at European institutions such as the University of Berlin, University of Göttingen, L’Ecole Polytechnique, Cambridge University, and Oxford University. Indeed, until Adolph Hitler came to power, German universities were considered the best in the world. Afterwards, there was a great intellectual migration out of Germany, mainly to the United States. Consequently, as Cole relates, “Today, there is not one German university in the world’s top 50.” Meanwhile, since the 1930s, roughly 60 percent of Nobel Prizes have been awarded to scholars at American institutions.10

• International students: American higher education represents one of the few sectors of the U.S. economy with a favorable balance of trade. We attract talented young people from around the world who seek opportunities at American universities as students, scholars, and scientists. As shown in Figure 3-1, the United States has the largest market share of foreign students in tertiary education. That share has been shrinking in recent years, but may be on the rise again with increases in Chinese undergraduates at American institutions. As seen in Figure 3-2, a very high percentage of these intellectual migrants stay here and work in science, technology, engineering, and mathematics occupations.

• Global rankings: There are numerous global rankings of research universities and substantial debates about the indicators useful in compiling them. While we do not endorse any particular ranking or methodology, we do note that in almost every case they indicate the general dominance of U.S. institutions. For example, as shown in Box 3-2, the most recent Academic Ranking of World Universities (ARWU) produced

<<FIGURE OMITTED>>

at Shanghai Jiao University (2010), placed 8 U.S. institutions in the top 10, 17 in the top 20, 35 in the top 50, and 54 in the top 100.11

• Productivity: Jonathan Cole argues that “we are the greatest because we are able to produce a very high proportion of the most important fundamental knowledge and practical research discoveries in the world.”12 This can be glimpsed, for example, in the indicators used in the ARWU, as shown in Table 3-1, that emphasize publications and citations and, in particular, the number of highly cited faculty in an institution. It can also be seen in, as shown in Box 3-3, the Organisation for Economic Co-operation and Development’s Science, Technology, and Industry Scoreboard 2011, which demonstrates that, “as measured by normalised citations to academic publications across all disciplines, 40 of the world top 50 universities are located in the United States, with some U.S. universities excelling in a wide range of disciplines.”13

Our preeminence can be seen not just in these indicators, but in the

<<FIGURE OMITTED>>

actions of others. Leaders in nations around the world are reshaping their universities to compete with ours by emulating them and our system. For example, in the Bologna Process, the Council of Europe in conjunction with the European Commission is reforming European higher education, including doctoral education, across **47** countries. The goal of the process is to improve Europe as a knowledge society. The strategies of the process include greater harmonization of degrees across nations; a greater convergence with the U.S. model to promote quality, easier interaction with the United States, and attractiveness to non-European students; and an increase in the overall competitiveness of European higher education.14

Second, reports of specific institutions have demonstrated their significant economic impact locally, regionally, and **nationally**, as talented graduates of these institutions have created and populated many new businesses that go on to employ millions of Americans. For example, Jonathan Cole notes:

Stanford University reports, for example, that faculty members, students, and alumni have founded more than 2,400 companies—and a subset, including Cisco Systems, Google, and Hewlett-Packard, generated $255-billion of total revenue among the “Silicon Valley 150” in 2008.

and

The Massachusetts Institute of Technology (MIT) has reported that 4,000 MIT-related companies employ 1.1 million people and have annual world sales of $232-billion—a little less than the gross domestic product of South Africa and of Thailand, which would make MIT companies among the 40 largest economies in the world.15

Meanwhile, to provide the example of a public institution that has been significantly supported by the federal government and its state, the University of Alabama (UAB) Birmingham reports:

• $4.6 billion in total economic impact is generated by UAB in the state of Alabama.

• $1 invested by the state in UAB generates $16.23 in the total state economy.

• 61,205 jobs are supported in the state of Alabama.

• $302.2 million is generated in state and local tax revenue.

The UAB report asserts further that “the economic and employment impact of UAB’s expansion in 2020 (mid-range scenario) is projected to grow to $6.6 billion, generate 72,449 jobs and create $431.4 million state and local tax revenue.”16 These impacts are generated by just three diverse institutions. Expand this to 120 or more institutions and the impact grows enormously.

Third, examples of specific products and companies demonstrate the economic and social impact and penetration of the results of university education and research. For example, Jonathan Cole summarized many of the examples in his book as follows:

The laser, magnetic-resonance imaging, FM radio, the algorithm for Google searches, global-positioning systems, DNA fingerprinting, fetal monitoring, bar codes, transistors, improved weather forecasting, mainframe computers, scientific cattle breeding, advanced methods of surveying public opinion, even Viagra had their origins in America’s research universities. Those are only a few of the tens of thousands of advances, originating on those campuses that have transformed the world.

<<FIGURE OMITTED>>

“Such discoveries, he writes, “have provided industry with the material needed for the growth of new, high-**technology** businesses—and universities have trained most of the highly **skilled work force** that populates our major industrial laboratories.”17

To add to Cole’s list, the National Science Foundation and the Science Coalition have also catalogued how federal funding for research, and in particular, for research performed in universities, has led to important products, companies, and jobs. Box 3-4 provides a partial list of NSF’s Sensational 60 products that resulted from or drew on research the foundation funded.18 The Science Coalition report, meanwhile, provides details on the origin, size, and revenue of 100 successful companies, just a small sample of the many that have grown out of federally funded uni-versity research. Some of these companies are well known, like Google and SAS. Google, of course, grew out of research on a better search engine at Stanford University funded by the National Science Foundation. Others, like Sharklet Technologies of Alachua, Florida, or A123 Systems of Watertown, Massachusetts, are not yet household names but contribute importantly to their local economies. A123, which grew out of materials research at MIT funded by the U.S. Department of Energy, now employs 1,740 people and had annual revenue in 2008 of $54 million. What conveys the power of university research, perhaps even more than the data on the 100 companies that can be reviewed in the coalition report, are the quotes in Box 3-5 from company founders that demonstrate, through their own words, how important it can be for jobs, economic growth, and the outcomes for the health, security, or quality of life for Americans that their products bring.

Research in the social, behavioral, and economic (SBE) sciences also contribute to critical national goals. As a recent report from the National Science and Technology Council contends, “The quest for deeper understanding of humans is key to managing society’s most critical challenges.” It continues by noting:

These challenges include:

• Developing more effective education programs

• Developing better health care programs

• Understanding violence, suicide, abuse, neglect, addiction, and mental illness

• Mitigating fanaticism, extremism, and terrorism

• Protecting confidentiality and privacy

• Fostering societal resilience in the face of both natural and human-made disasters

• Fostering a culture of creativity and innovation and maintaining America’s competitiveness in an era of rapid globalization

• Addressing the long-term sustainability of civilization within Earth’s ecosystems.

These challenges all share a human element, which makes them resistant to untested interventions or technological solutions, and makes evidence-based policy making difficult. After a half-century of progress, however, the SBE sciences can offer more rigorous, evidence-based strategies to address this human element.19

**They facilitate sustainable development.**

**Sarpong 24** [Reagan; Professor of the Maharaja Sayajirao University of Baroda; “Research and Innovation in Higher Education: Promises of Generative Artificial Intelligence for Sustainable Development,” https://www.researchgate.net/publication/387335205\_Research\_and\_Innovation\_in\_Higher\_Education\_Promises\_of\_Generative\_Artificial\_Intelligence\_for\_Sustainable\_Development; DOA: 2-13-2025] sumzom

In these uncertain yet promising times, knowledge societies offer fresh opportunities for human and sustainable development (UNESCO, 2005). Since capital, natural resources, and labour are no longer the sole economic resources (Ondari-Okemwa, 2011), **knowledge** has emerged as a **significant economic**, **political**, and **cultural asset**. As such, knowledge creation is **crucial** for progress of knowledge societies. Higher education‘s capacity to create and **transform knowledge** makes it crucial for the **development** of knowledge societies (Marylouise, 2009). Higher education serves as a significant cultural and scientific resource, fostering human development and driving **economic**, **technological**, and **societal transformation**. By promoting knowledge sharing, research, and innovation, higher education equips students with the skills necessary to thrive in dynamic labour markets (UNESCO, 2023). Its keen interest in **research** and innovation establishes it as a **pivotal** player in **sustainable development** (Muresan & Gogu, 2012).

**Higher education institutions** are **essential** platforms through which higher education contributes to **knowledge** generation and **sustainable development** (Muresan & Gogu, 2012). These institutions undertake responsibilities in teaching and learning, **research**, and community engagement. Research within these institutions acts as a **catalyst** for innovation and advancement, fostering economic **growth** and **competitiveness** (Hasan, 2023). Their research and innovation activities enable direct contributions to a country's growth and productivity (Bradley et al., 2008; Moyle, 2010). Consequently, the involvement of higher education institutions (HEIs) in research and innovation is critical for advancing societies and economies (Satapathy & Malhotra, 2020).

Given the critical role of higher education institutions in research and innovation, it is imperative they actively rise to the occasion. The **world** faces challenges such as **climate change**, **pandemics**, **conflict**, **inequality**, **technological change**, **urbanization**, and **migration** (United Nations, 2020; World Bank, 2023). Additionally, many developing countries **struggle** with **declining growth** prospects, **weak investment**, and **increasing debt**, which **undermines** progress toward **Sustainable Development Goals** and exacerbates poverty and inequality (World Bank, 2023). Therefore, all stakeholders, including researchers, university management, policymakers, and industry decision-makers, must focus on maintaining highquality, effective, and relevant research and innovation (Furusten, 2023). Higher education institutions are expected to **drive** innovation and **research** across a broad **spectrum** of **global issues** (Sridhara, 2023), fostering a culture where **students** are encouraged to explore and **present** outcome-based **ideas** to the industry (Vincent & Antonysamy, 2023).

Promoting culture of research and innovation is crucial for institutional success (Ahmed, 2023). One effective technique to promote a culture of research and innovation within an institution is to use Information and Communication Technology (ICT) and interactive technologies to increase student participation and facilitate learner-centered approach (Ahmed, 2023). ICT enables higher education institutions to coordinate research within an innovation ecosystem to address social and business issues and expand knowledge societies (Ho, 2007). Open Sources and Open Standards facilitated by ICT can accelerate research and innovation. For instance, the Blue Brain project, a ground breaking effort to reverse-engineer the mammalian brain for better understanding of brain function and malfunction through simulations on High-Performance Computing (HPC), would not be possible without ICT (Ho, 2007).

The knowledge-driven world, enabled by emerging technologies, is global and multidisciplinary (Blass & Hayward, 2014). The upcoming decade is expected to witness **significant shifts** in how research is **developed**, **executed**, and **communicated** as a result of technological advancements and new generational ideas (Elsevier & Ipsos MORI, 2019). These put further pressure on research ecosystems to innovate, resulting in a revolution in research practices. The advent of new research practices and transformations in society, technology, economy, environment, policy, values, and cultures is altering the research and innovation landscape. Research and innovation are becoming more **global** and interconnected, resulting in a multipolar world. Communities of scientists and technology developers conduct research and innovation activities in various locations, facilitated by networking, digitalization, and virtualization through ICTs. The expanding role of business in research and innovation is becoming more international. Additionally, citizens, funding agencies, policymakers, the media, and volunteer organizations are joining the traditional list of stakeholders in research and innovation. These trends present new opportunities and uncertainties about how research and innovation will be initiated, organized, and conducted in the future (Amanatidou et al., 2016).

To achieve more realistic, efficient and sustainable research and innovation systems, models such as the digital university, agile university, virtual university, smart university, eUniversity, and university 4.0 have been developed mainly due to the digitalization of education and research. For example, University 4.0 aims to "leverage the campus as a testbed for sustainability" (MIT Sustainability Office, n.d.), involving faculty, staff, researchers, and students in the process and using rapid prototyping methodologies to find **local solutions** to **global sustainability challenges** (Giesenbauer & Müller-Christ, 2020). Advances in research are increasingly the result of collaboration among experts spread across various laboratories in a country or globally, often requiring the sharing of rare, complex, and expensive equipment. The creation of a virtual laboratory, a "laboratory without walls" that fully utilizes ICT, is often the best solution (Angelino, 2002).

The development of these models has brought **significant benefits** in terms of broadening students' **knowledge base** and enhancing their **confidence** to compete in a dynamic environment (Rastogi, 2019). Some educators and technology evangelists believe that higher education will eventually become fully digital supported by artificial intelligence (AI) and virtual reality (VR) (Siemens, 2023).

AI technology is now a common part of everyday life, with its applications spanning multiple sectors. Manufacturing, banking, healthcare, and agriculture have all adopted AI to improve operations, reduce costs, and enhance efficiency. For instance, predictive maintenance enabled by AI algorithms has revolutionized industry by reducing downtime and saving billions of dollars annually (Gross, 2023). **Scholars** in higher education use **AI** for a variety of **research**-related tasks, such as searching, writing, proofreading, translating texts, identifying and summarizing sources, **data analytics**, data visualization, data and text mining, coding, and more (Yaroshenko & Iaroshenko, 2023). Significant advances in weather prediction and research are also being made using AI applications, with the University of Oklahoma as one example (Delozier, 2023). However, traditional AI is limited by its reliance on predefined rules and lacks creativity in developing new solutions or approaches. Its strength lies in making strategic decisions within well-defined boundaries rather than exploring new territories. In essence, it does not generate new content, limiting its ability to drive research and innovation forward (Data & Analytics, 2023).

**Generative artificial intelligence** (Gen AI) is beginning to reveal its disruptive **potential** (Agrawal et al., 2023). This global technological advancement is **transforming** various industries, including **education** and **research** (Tchoffo, 2023). Unlike previous AI breakthroughs that focused on automating physical tasks, Gen AI is expected to enhance **automation** in knowledge work thanks to its **linguistic capabilities** (both human and computer languages) (J.M. Financial, 2023). Exploring Gen AI promises a world where technology enables new dimensions of **human creativity** (Data & Analytics, 2023). It is anticipated that Gen AI will be a stimulant for **research** and innovation, potentially contributing to knowledge societies and **sustainable development** (Tchoffo, 2023). Although this technology is still in its infancy, with its widespread applications gradually emerging (J.M. Financial, 2023), only a few institutions have begun to implement it (Agrawal et al., 2023). There is broad agreement that acting **now** is the right move. There is also awareness that failure to innovate is not an option (Coffey, 2023). Therefore, higher education institutions must consider **investing early** in the necessary infrastructure and manpower to embrace **Gen AI** in order to harness their capacity to contribute to knowledge societies while providing actionable solutions to sustainable development challenges. This chapter focuses on leveraging Gen AI‘s potential to transform research and innovation across higher education for sustainable development. It highlights research and innovation in higher education, investments toward better research and innovation ecosystems in different countries, recent developments of generative AI in research and innovation systems of HEIs, returns on investments on application of generative AI in research and innovation systems and implications for practice.

Research and Innovation in Higher Education

Higher education plays a crucial role in society by enhancing skills and fostering creativity, essential for long-term development and societal resilience. Its primary objectives are to create, disseminate, and preserve knowledge. Higher education uniquely contributes through the **integration** of **research**, innovation, and other activities (Royal Irish Academy Higher Education Futures Taskforce, 2021). Research generates new knowledge, refines existing theories, and deepens our understanding of the world (Ho, 2007: 3; Meek & Davies, 2009: 65). When knowledge is applied innovatively to produce new outcomes, research and knowledge production become innovation, with the associated intellectual property adding value to businesses and the economy (Blass & Hayward, 2014). Innovation involves creating and developing new products or services to enhance efficiency and effectiveness (Satapathy & Malhotra, 2020). It is a recombinant process that leverages existing knowledge to create new goods, processes, services, and markets (Atuhaire et al., 2022), underscoring the vital role of research and innovation in national development (Ighalo & Ighalo, 2018).

**Research** and innovation offer a **wide range** of **benefits**, including improving **population health** and **well- being**, **generating evidence-informed policy**, **driving societal** and **cultural change**, strengthening indigenous companies, securing **foreign direct investment** (FDI), and safeguarding cultural heritage for future generations (Royal Irish Academy Higher Education Futures Taskforce, 2021). They also **enhance teaching** and learning by promoting **innovative approaches** and allowing educators and students to experiment with **new ideas** and technologies (AranibarRamos et al., 2023). **Research** and innovation can **empower** young people facing unemployment to become **economic contributors** by providing them with the **knowledge** and **skills** needed for socio-economic participation and benefit (Atuhaire et al., 2022).

Given the challenges posed by **climate change**, **research** and innovation are **critical** for **transitioning** to a **green**, digital, and sustainable knowledge-based **economy** and society, contributing to economic growth, recovery, and environmental sustainability. A robust public research and innovation system is a strategic asset and part of the global ecosystem, fostering economic and social progress at regional, national, and international levels. Enhancing diversity, equality, and inclusion (DEI) in higher education institutions is essential for a vibrant research and innovation environment (Royal Irish Academy Higher Education Futures Taskforce, 2021). Thus, creating a positive academic atmosphere at HEIs is crucial for providing quality education that meets the aforementioned goals. It also keeps faculty members and students engaged, thereby initiating and catalysing high-quality research and innovation (Lakhotia, 2021).

**Sustainability is necessary to avoid extinction.**

**Cernev 20** [Tom; Australian National University, Canberra, Australia; Richard Fenner; Centre for Sustainable Development, Cambridge University Engineering Department, UK; January 2020; "The importance of achieving foundational Sustainable Development Goals in reducing global risk", ScienceDirect; https://www.sciencedirect.com/science/article/abs/pii/S0016328719303544 DOA: 2-13-2025] sumzom

4.2 Existential and Catastrophic Risk

The level and consequences of these risks may be severe. Existential Risks (ER) have a wide scope, with extreme danger, and are “a risk that threatens the premature extinction of humanity or the permanent and drastic destruction of its potential for desirable future development” (Farquhar et al., 2017,) essentially being an event or scenario that is “transgenerational in scope and terminal in intensity” (Baum & Handoh, 2014). With a smaller scope, and lower level of severity, global catastrophic risk is defined as a scenario or event that results in at least 10 million fatalities, or $10 trillion in damages (Bostrom & Ćirković, 2008). Global Catastrophic Risk (GCR) events are those which are global, but they are durable in that humanity is able to recover from them (Bostrom & Ćirković, 2008; Cotton-Barratt et al., 2016) but which still have a long-term impact (Turchin & Denkenberger, 2018b).

Achieving the Sustainable Development Goals can be considered to be a means of reducing the long-term global catastrophic and existential risks for humanity. Conversely if the targets represented across the SDGs remain unachieved there is the potential for these forms of risk to develop. This association combined with the likely emergence of new challenges over the next decades (Cook et al., 2014) means that it is of great value to identify points within the systems representations of the Sustainable Development Goals that could both lead to global catastrophic risk and existential risk, and conversely that could act as prevention, or leverage points in order to avoid such outcomes. This identification in turn enables sensible policy responses to be constructed (Sutherland & Woodroof, 2009).

Whilst existential threats are unlikely, there is extensive peril in global catastrophic risks. Despite being lesser in severity than existential risks, they increase the likelihood of human **extinction** (Turchin & Denkenberger, 2018a) through **chain reactions** (Turchin & Denkenberger, 2018a), and inhibiting humanity’s response to other risks (Farquhar et al., 2017). It is necessary to consider risks that may seem small, as when acting together, they can have extensive consequences (Tonn, 2009). Furthermore, the high adaptability potential of humans, and society, means that for humanity to become extinct, it is most likely that there would be a **series** of events that culminate in extinction as opposed to one large scale event (Tonn & MacGregor, 2009; Tonn, 2009).

Whilst the prospect of existential risk, or global catastrophic risk can seem distant, the Stern Review on the Economics of Climate Change estimated the risk of extinction for humanity as 0.1% annually, which accumulates to provide the risk of extinction over the next century as 9.5% (Cotton-Barratt et al., 2016). With respect to identifying these risks, it is known that in particular, “positive feedback loops… represent the **gravest** existential risks” (Kareiva & Carranza, 2018), with pollution also having the potential to pose an existential risk.

With respect to reinforcing feedback loops, there is particular concern about the effects of time delay, and the level of uncertainty when feedback loops interact (Kareiva & Carranza, 2018). It is difficult to identify the exact thresholds that are associated with tipping points (Moore, 2018), which leads to global catastrophic risk or existential risk, and thus it is necessary to understand the events that can lead to existential risks (Kareiva & Carranza, 2018).

Table 4 identifies possible global catastrophic risks and existential risks as reported in the literature and from Figure 3 these are aligned to the Sustainable Development Goals they impact the most.

4.3 Linking risks with progress in the SDGs

Generally it is the Outcome/Foundational and Human input SDGs that are most directly related. For example as the movement of refugees increases pandemic risk, poverty levels in low and middle income countries increase reducing the health of the population, and so restricting access to education which further enhances poverty and birth rates rise as family sizes increases generating **unsustainable population** growth which furthers the migration of refugees (Figure 5). Figure 3 shows that leverage points to reduce refugees lies in SDG 16 (Peace Justice and Strong Institutions), reducing malnutrition through alleviating SDG 2 (Zero Hunger) and taking SDG 13 (Climate Action) to avoid the mass movement of people to avoid the impacts of global warming.

Global warming itself will drive disruptive changes in both terrestial and aquatic ecosystems affecting SDG 15 (Life on Land) and SDG 14 (Life Below Water) adding to their vulnerability to increases in pollution driven by a growing economy. Loop B (in Figure 4) shows the constraints associated with SDG 13 (Climate Action) may slow the economic investment in industry and infrastructure reducing the pollution generated, encouraging adoption of SDG 7 (Affordable and Clean Energy) whilst stimulating carbon reduction and measures such as afforestation, which will also improve the foundational environmental goals.

Depletion of resources and biodiversity are strongly linked to SDG 12 (Responsible Consumption and Production) through measures such as halving global waste, reducing waste generation through recycling reuse and reduction schemes, and striving for more efficient industrial processes. The more resources that are used, the less responsible is Consumption and Production which may thus reduce biodiversity (Figure 3) and increase the amounts of wastes accumulating in the environment.

The final driver of Global Catastrophic Risk is an agricultural shortfall which will increase global **Hunger** (SDG 2) and widen the **Inequality** (SDG 10) between rich and poor nations and individuals. Quality Education (SDG 4) is important as a key leverage point to stimulate the generation and adoption of new technologies to improve energy (SDG 7) and water supplies (6) which can enhance agricultural production. Such linkages are convincingly examined and demonstrated in the recent film “The Boy Who Harnessed the Wind” (2019), based on a factual story of water shortages in Malawi in the mid 2000s.

These examples may appear self evident, but it is the connections between the goals and how they adjust together that is important to consider so the consequence of policy actions in one area can be fully understood. Because of the underlying system structures global threats can quickly transmit through the system. Water Crises will limit the water available for agriculture and basic needs which in turn will stimulate a decline in Gender Equality (SDG 5). Technology disruption from cyber attacks will restrict the ability to operate Sustainable Cities and Communities (SDG 11) and potentially expose populations to extreme events by disrupting transport, health services, and the ability to pay for adaptation and mitigation of climate related threats from a weakened economy. Conflict (in all forms) will increase refugees and climate change provides the backdrop against which all these interactions will play out.

Whilst it is possible that general catastrophic risk or existential risk scenarios may eventuate from the non-achievement of the Sustainable Development Goals, there are certain aspects within the causal loop diagram which if prioritised will reduce this risk. For example, to reduce the risk of pandemic, ensuring that the number of Refugees is minimised, and is a leverage point. Similarly, prioritising SDG 3 (Good Health and Wellbeing) is essential and is enabled by many of the other goals. However, a feature missing from the SDGs is a recognition of the precautionary principle, with an implicit assumption that technological innovation alone may create improvements in many of the goals.

**Research on militarized conflicts can avert nuclear war.**

**D'Orazio ’24** [Vito D'Orazio; associate professor, political science and data sciences, WVU Eberly College of Arts and Sciences, 6-6-2024, " WVU research reveals patterns behind armed conflicts, bolstering national security", WVU Today, https://wvutoday.wvu.edu/stories/2024/06/06/wvu-research-reveals-patterns-behind-armed-conflicts-bolstering-national-security] mac

West Virginia University research is **strengthening national security** by ensuring policymakers, military institutions, think tanks, academics and journalists have access to **substantial, up-to-date information** on international conflicts when they need it.

A $555,647 grant from the National Science Foundation supports the three-year expansion of the Correlates of War Project’s Militarized Interstate Dispute Data, led by Vito D’Orazio, associate professor of political science and data sciences at the WVU Eberly College of Arts and Sciences.

In a militarized interstate dispute, or MID, one country or nation-state directs the threat, display or use of armed force toward another state. These international interactions invoke the military but fall short of war. For example, in December 1994, an American helicopter was shot down by North Korea. This incident was part of a larger dispute involving North Korea, South Korea and the United States in the 1990s. Despite this and many incidents involving the military, the dispute did not escalate to war.

“**Insight** into militarized disputes between states **is critical**, given the **reemergence** of long-term strategic **competition between the U.S. and other global powers**, along with the **rapid dispersion of new technologies into domains of confrontation**,” D’Orazio said.

“Data on these events allow interested parties to **analyze when low-hostility incidents**, such as border fortifications or troop mobilizations, are **likely to escalate to higher levels of hostility** or to be managed short of that point. **Understanding patterns** of conflict escalation and de-escalation **is critical for informed decision-making**.”

The Correlates of War Project began compiling data on these disputes in the 1980s, and the dataset’s fifth edition was released in 2020. D’Orazio called the scope of the data “massive,” explaining that it currently incorporates all MIDs worldwide from 1816 to 2014.

The sixth update will add data spanning 2014-2024 and will launch a new component called MID Live, an early detection mechanism for interstate hostilities. MID Live uses near real-time incident detection to identify militarized interstate disputes as they happen and publicize them via the X account @mids\_proj.

According to D’Orazio, the early release of information about potential militarized disputes can **improve conflict forecasting** models and monitoring systems even when the information is **not perfect** or **fully vetted**.

“Our work reveals **evolving patterns of conflict and competition** between states as well as **opportunities for cooperation**,” he said. “It helps to lay the basis for **effective and informed security policies and strategies**.”

Before the first collection of MID data in the 1980s, researchers had very little data to study the militarized disputes that didn’t escalate to war. Since then, MID data have been used to answer questions and **guide policies** relevant to natural **resource competition**, **territorial disputes**, **arms races**, **crisis escalation**, **conflict contagion**, **nuclear weapons**, **domestic protest**, **regime transitions**, **peacebuilding** and **climate change**, among other issues.

“One way MID data have been used is to study a theory called ‘the democratic peace,’ which proposes that democratic countries do not go to war against each other,” D’Orazio said. “U.S. presidents commonly support the democratic peace, with Bill Clinton stating, ‘Democracies don’t attack each other,’ and George W. Bush saying, ‘Democracies don't go to war with each other.’ MID data have provided academics with much of the quantitative evidence for evaluating those statements.”

The data categorizes disputes with information about participants, dates, fatalities and military action. The dataset also indicates information such as the dispute’s outcome — a win or yield by either side, a stalemate or compromise, the release of people or objects, or an unclear resolution — and whether any settlement was negotiated or imposed.

The researchers will work with students in England, Arizona and West Virginia, as well as U.S. Air Force cadets in Colorado. They will identify militarized disputes from a wide range of international news sources, classify the incidents, and document them according to the dates, fatalities, types of action and motivations involved.

At WVU, PhD students are already participating in the project, which offers research opportunities to WVU undergraduates as well.

“Because of the students’ and cadets’ **participation** in this project, members of the next generation of scholars and Air Force leaders will become **deeply familiar** with the **intricacies** of interstate **hostilities**,” D’Orazio said.

“Currently, we’re seeing a resurgence of major power competitions and interstate hostilities across the globe. With our new militarized interstate dispute data, researchers and leaders will have a nuanced look at the elements that contribute to decision-making and the design of national security policy and strategy.”

#### Otherwise, Extinction.

**Sarg 15** — (Stoyan Sarg, Director of the Physics Research Department at the World Institute for Scientific Exploration, 10-9-2015, "The Unknown Danger of Nuclear Apocalypse", Foreign Policy Journal, https://www.foreignpolicyjournal.com/2015/10/09/the-unknown-danger-of-nuclear-apocalypse/, accessed 2-7-2025) //TH

With the new NATO plan for installation of nuclear tactical weapons in Europe, nuclear missiles may reach Moscow in only 6 minutes, and the opposite case is also possible in the same time. The question is: how can we be sure that this will not be triggered by a human error or computer malfunction. An adequate reaction dictated by the dilemma “to be or not to be” and the concept of preventive **nuclear strike** may lead to a nuclear consequence that is difficult to stop. At the present level of distributed controlled systems and military global navigations, this will lead to **unstoppable global nuclear war**. However, there is something not predicted, of which the military strategists, politicians and powerful forces are not aware. Probably, it will **not** be a **nuclear winter** that they hope to survive in their **underground facilities**. The **most probable** consequence will be a **partial loss** of the **Earth’s atmosphere** as a result of one or many **powerful simultaneous tornadoes** caused by the **nuclear explosions**. In a tornado, a powerful **antigravitational** effect takes place. The official science does not have an adequate explanation for this feature due to an incorrect concept about space. The antigravitational effect is not a result of the circling air. It is a specific physical effect in the aether space that is dismissed in physics as it is currently taught. Therefore, the effective height of this effect is not limited to the height of the atmosphere. Then in the case of many simultaneous **powerful tornadoes**, an **effect** of **suction** of the **earth atmosphere into space** might take place. Such events are **observed on the Sun** and the present physical science does not have an explanation for them. The antigravitational effect is accompanied by specific electric and magnetic fields with a twisted shape. This is observed in tornado events on the Sun. Some effects in the upper Earth atmosphere known as sprites have a similar combination of electrical and magnetic fields but in a weaker form. They are also a mystery for contemporary physical science. At the time of **atmospheric nuclear tests**, made in the last century, a number of **induced tornadoes** are observed near the **nuclear mushroom** as shown in Figure 1. The strongest anti gravitational effect, however, occurs in the central column of the formed nuclear mushroom. The analysis of underwater nuclear tests also indicates a strong anti gravitational effect. It causes a rise of a vertical column of water. In the test shown in Figure 2, the vertical column contains millions tons of water. Thermonuclear bombs are **multiple times more powerful**. The largest thermonuclear bomb of the former Soviet Union tested in 1961 is 50 megatons. It is 3,300 times more powerful than the bomb dropped by USA on Hiroshima at the second world war and may kill millions. It is known that Mars once had liquid water and consequently an atmosphere that has mysteriously disappeared. If the scenario described above takes place, the Earth will become a **dead planet like Mars**. The powerful politicians, military adventurers and their financial supporters must be aware that even the most secured **underground facility** will not save them if a global nuclear conflict is triggered. Their disgraced end will be more miserable than the deaths of the billions of innocent human beings, including the animal world.

**2AC**

## 2AC---AT: Critical Thinking

**Intelligent 23** --- (Intelligent, 10-24-2023, "New Survey Finds Students Are Replacing Human Tutors With ChatGPT", https://www.intelligent.com/new-survey-finds-students-are-replacing-human-tutors-with-chatgpt/) //doa2-28-2025 + master chen 💆

New Survey Finds Students Are Replacing Human Tutors With ChatGPT Last Updated: October 24, 2023 facebook twitterflipboardemail As students graduating this spring have had access to ChatGPT for almost an entire school year, we wanted to learn more about their experiences with ChatGPT and how it compares to studying in a more traditional way. When we surveyed college students in January 2023, just a few months after ChatGPT became available, close to one-third had already reported using the tool to complete written assignments. In May, Intelligent.com surveyed 3,017 high school and college students (ages 16-24) along with 3,234 parents of younger students to learn more about student study habits over this past academic year. Ten percent of high school and college students aged 16-24 say they studied with both ChatGPT and a tutor this past academic year, while 15% of parents with school-aged children say their kids did the same. We found, of students who studied this past academic year with a tutor and ChatGPT: Nearly all have replaced some of their tutoring sessions with ChatGPT **95% say their grades have improved since studying** with ChatGPT **9 in 10 prefer studying with ChatGPT over studying with a tutor** Most common subjects students have replaced tutors for are math and science Students Find Studying with ChatGPT to Be More Effective Than Studying with a Tutor Of students who had the opportunity to directly compare studying with ChatGPT vs. a tutor over the past academic year, the vast majority report a preference for ChatGPT. “As a current student using ChatGPT, I have found it to be a helpful and convenient tool for studying,” says college Junior Johnson Adegoke. “Unlike seeing a tutor, **ChatGPT is available 24/7** and can answer my questions immediately,” he continues. “Plus, I can study at my own pace and review the information as many times as I need to. While it’s not quite the same as having a human tutor, I appreciate the accessibility and flexibility that ChatGPT offers,” he explains. Eighty-five percent of high school and college students surveyed say studying with ChatGPT is more effective than studying with a tutor. This number is higher for parents of school-aged children, 96% of whom say that studying with ChatGPT is more effective than studying with a tutor for their children. Write-in responses from students and parents of students who believe ChatGPT is more effective included the following: “ChatGPT’s ability to correct mistakes makes it easier for children to learn correctly.” “More **relaxed**, more **efficient**.” “ChatGPT can provide timely feedback on students’ learning progress and performance, and help students adjust their learning direction and methods.” Of respondents who believe tutoring is still more effective than ChatGPT, reasons included: “Tutors can communicate face to face, which artificial intelligence cannot do.” “Mentors can stimulate students’ interest in a variety of ways, including encouragement, discussion, and practice.” “Because studying with tutors can build good teacher-student relationships and trust, promote effective interactive learning and feedback, and make it easier for children to understand and absorb knowledge.”

**[1] DL. That’s why**

**Kelly 23** --- (Samantha Murphy Kelly, [reporter @ CNN], 12-13-2023, "ChatGPT did not increase cheating in high schools, Stanford researchers find", https://www.cnn.com/2023/12/13/tech/chatgpt-did-not-increase-cheating-in-high-schools/index.html) //doa2-23-2025 + master chen 💆at 12:59 AM

When ChatGPT launched late last year, some high schools quickly developed strict policies to prohibit students from using the powerful AI chatbot tool over fears of cheating on assignments. But now a new study from researchers at Stanford reveals the percentage of high school students who cheat remains statistically unchanged compared to previous years without ChatGPT. The university, which conducted **an anonymous survey** among students at 40 US high schools, **found** about 60% to 70% of students have engaged in **cheating** behavior in the last month, anumber that **is the same or even decreased slightly since the debut of ChatGPT,** according to the researchers. In November 2022, ChatGPT -– developed by OpenAI –- went viral for generating convincing responses and essays in response to user prompts in seconds. While ChatGPT and similar AI tools have gained traction, the technology has raised some concerns over inaccuracies and its potential to perpetuate biases, spread misinformation and enable plagiarism. “While there are individual alarming cases in the news about AI being used for cheating, we are seeing **little evidence that the needle has moved for high schoolers overall,**” Victor Lee, Stanford’s faculty lead for AI and education who helped oversee the survey, told CNN. The findings come as research center Pew recently reported only 19% of teens ages 13 to 17 have used the platform for schoolwork. (And only two-thirds of teens have heard of ChatGPT). Lee said the number of students accessing ChatGPT could change in the future as they learn more about the technology. The survey also revealed students believe the tool should be allowed for “starter” purposes with assignments, such as asking it to generate new concepts or ideas for an assignment. Most of the respondents, however, agreed it should not be used to write a paper. “It shows that a **majority of students truly want to learn and see AI as a way to help them** – as opposed to seeing it only as a **tool** to ‘do school’ and cut corners or save time as they **complete assignments,”** said Denise Pope, a senior lecturer at Stanford’s Graduate School of Education who also helped oversee the survey. Some of the main cited reasons why students cheat include struggling to grasp subject material, not having enough time to do homework and feeling pressured to perform well, according to the researchers. “We are only a little over a year into ChatGPT capturing public attention, so we all should expect some shifts over time with schools, work, and daily life,” Lee said. “A lot **depends** on how **schools** choose to **approach AI** as a topic and a **tool**, which could move things in **either direction**.” Pope said educators should consider inviting student voices into these conversations, calling them “insightful and thoughtful” on the topic of AI and cheating. In a recent panel discussion, the researchers said students talked through the purpose of learning to write and debated what else they should be learning in school as AI continues to emerge. “That allowed all of us in the discussion to talk about the role of schools moving forward in a world where AI is ubiquitous,” she said. School responses In the first few months after the release of ChatGPT, fears over cheating escalated. Public schools in New York City and Seattle were among the first institutions to ban students and teachers from using ChatGPT on the district’s networks and devices Some college-level instructors told CNN at the time they shifted back to in-classroom essays for the first time in years, and others required more personalized essays. Others said students were also required to film short videos that elaborate on their thought process. Nowadays, however, more schools are encouraging and even teaching students how to best use these tools. Vanderbilt University, for example, is an early leader taking a strong stance in support of generative AI by offering university-wide training and workshops to faculty and students. A three-week 18-hour online course offered this summer was taken by over 90,000 students. With more experts expecting the continued application of artificial intelligence, professors fear ignoring or discouraging the use of it will be a disservice to students and leave many behind when entering the workforce. “It cannot be ignored,” Jules White, an associate professor of computer science at Vanderbilt University, previously told CNN. “I think it’s incredibly important for students, faculty and alumni to become experts in AI because it will be so transformative across every industry in demand so we provide the right training.” Although concerns around cheating still exist, White said he believed students who want to plagiarize can still seek out other methods such as Wikipedia or Google searches. Instead, he said students should be taught that “if they use it in other ways, they will be far more successful.” Stanford also offers an online hub with free resources to help teachers explain to high school students the dos and don’ts of using AI. In the meantime, the researchers said they will continue to collect data throughout the school year to see if they find evidence that more students are using ChatGPT for cheating purposes. “The jury is still out, but our current data shows that students don’t necessarily want to use it to short-cut learning as much as they want to use it to enhance their learning,” Pope said.

**Thus, Zhou conclude 53 percent test scores**

**Sun and Zhou 24** — (Lihui Sun and Liang Zhou, 8-27-2024, "Does Generative Artificial Intelligence Improve the Academic Achievement of College Students? A Meta-Analysis", Sage Journals, https://www.researchgate.net/publication/384834881\_Does\_Generative\_Artificial\_Intelligence\_Improve\_the\_Academic\_Achievement\_of\_College\_Students\_A\_Meta-Analysis, accessed 3-27-2025) //RIDGE PARTIAL DOUBLE OCTAFINALIST RAHUL RANI

The use of generative artificial intelligence (Gen-AI) to assist college students in their studies has become a trend. However, there is no academic consensus on whether Gen-AI can enhance the academic achievement of college students. Using a meta-analytic approach, this study aims to investigate the effectiveness of Gen-AI in improving the academic achievement of college students and to explore the effects of different moderating variables. **A total of 28 articles (65 independent studies, 1909 participants) met the inclusion criteria for this study.** The results showed that Gen-AI significantly improved college students’ academic achievement with a medium effect size (Hedges’s g = 0.533, 95% CI [0.408,0.659], p < .05). There were within-group differences in the three moderator variables, activity categories, sample size, and generated content, when the generated content was text ( g = 0.554, p < .05), and sample size of 21–40 ( g = 0.776, p < .05), the use of independent learning styles ( g = 0.600, p < .05) had the most significant improvement in college student’s academic achievement. The intervention duration, the discipline types, and the assessment tools also had a moderate positive impact on college students’ academic achievement, but there were no significant within-group differences in any of the moderating variables. This study provides a theoretical basis and empirical evidence for the scientific application of Gen-AI and the development of educational technology policy. **The** combined **effect** size **of Gen-AI** on college students’ **academic achievement is 0.533**, indicating that Gen-AI has a moderate contribution to college students’ academic achievement. This is **consistent with existing research**, where Baidoo-Anu and Owusu Ansah (2023) reported a **strong impact of Gen-AI on teaching and learning**, where **Gen-AI** significantly **improved** not only **the cognitive level, but also the critical thinking, creative thinking, and problem-solving skills** of college students (Vazquez- ´ Table 7. Effects of Intervention Duration on Effect Size. Moderator variables N Hedges’ g SE 95% CI Two-tailed test LL UL Z p Group differences Intervention duration 65 0.508 0.061 0.390 0.627 8.394 0.000 Q = 3.651 p = .455 <1 week 16 0.526 0.093 0.343 0.709 5.633 0.000 1–5 weeks 30 0.444 0.096 0.255 0.633 4.608 0.000 6–10 weeks 9 0.458 0.169 0.127 0.790 2.713 0.000 11–15 weeks 4 1.087 0.406 0.291 1.882 2.677 0.007 >15 weeks 6 0.848 0.329 0.202 1.493 2.573 0.010 Table 8. Effects of Generate Content on Effect Size. Moderator variables N Hedges’ g SE 95% CI Two-tailed test LL UL Z p Group differences Generate content 65 0.454 0.051 0.354 0.555 8.848 0.000 Q = 5.862 Code 9 0.473 0.097 0.283 0.663 4.876 0.000 p = .046 Image 2 0.248 0.103 0.047 0.449 2.413 0.016 Text 54 0.554 0.075 0.407 0.701 7.386 0.000 22 Journal of Educational Computing Research 0(0) Cano et al., 2021; Chang et al., 2022). At the same time, **Gen-AI also contributes to the development of non-cognitive aspects** of college students, **such as boosting confidence** (Essel et al., 2022; Sanchez-Ruiz et al., 2023 ´ ), **motivation and self-efficacy** (Kim & Lee, 2023). Overall, Gen-AI is effective in improving college students’ academic achievement, and this effect varies significantly depending on the moderating variables. If the moderating variables are properly combined, Gen-AI may be highly effective in improving the academic achievement of college students.

**Pomeroy 25** — (Ross Pomeroy [Writer @ Real Clear Science], 1-29-2025, "Does Using AI Wreck Your Critical Thinking Skills?", RealClearScience, https://www.realclearscience.com/blog/2025/01/29/does\_using\_ai\_wreck\_your\_critical\_thinking\_skills\_1087805.html, accessed 3-4-2025) //FK  
Generative AI is fantastic for brainstorming, showing prompters choices and ideas they might not have considered. **AI can also foster critical thinking when users hone the questions they are asking to achieve desired outcomes.** For example: trying to get an AI image generator to produce something that matches what you’re imagining. You have to be very clear and descriptive.

**[3c] AND,**

**Heaven 23** — (Will Douglas Heaven [*I am the senior editor for AI at MIT Technology Review, where I cover new research, emerging trends and the people behind them. Previously, I was founding editor at the BBC tech-meets-geopolitics website Future Now and chief technology editor at New Scientist magazine. I have a PhD in computer science from Imperial College London and know what it’s like to work with robots.*], 4-6-2023, "ChatGPT is going to change education, not destroy it", MIT Technology Review, https://www.technologyreview.com/2023/04/06/1071059/chatgpt-change-not-destroy-education-openai/, accessed 3-5-2025) //FK

One of her favorite uses of the technology is to bring more interactivity into the classroom. Teaching methods that get students to be creative, to role-play, or to think critically lead to a deeper kind of learning than rote memorization, she says. **ChatGPT can play the role of a debate opponent and generate counterarguments to a student’s positions**, for example. By exposing students to an endless supply of opposing viewpoints, **chatbots could help them look for weak points in their own thinking.**

Rose 23 — (Abstract null, xx-xx-xxxx, "Do gains in test scores explain labor market outcomes?", No Publication, https://www.sciencedirect.com/science/article/abs/pii/S0272775706000264, accessed 3-28-2025) //RIDGE PARTIAL DOUBLE OCTAFINALIST RAHUL RANI

Using data from the National Education Longitudinal Study of 1988, this article investigates whether students who made relatively large test score gains during high school had larger earnings 7 years after high school compared to students whose scores improved little. In models that control for pre-high school test scores, family background, and demographic characteristics, employed women who gain one standard deviation more than average are predicted to earn 9 percent more than average. These effects are even larger unconditional on employment status, indicating that test score gains influence both the employment status and earnings once employed. For men, **however, test score gains are not significantly related to employment status or earnings**, except for those men who have low initial test scores.

## 2AC---AT: Cost

**Google subsides - solves back for costs**

**Cai 25** — (Kenrick Cai [Journalist @ Reuters], 1-25-2025, "Google pushes global agenda to educate workers, lawmakers on AI", archive.is, https://archive.is/AdAqp, accessed 3-20-2025) //FK

**Google pushes global agenda to educate workers, lawmakers on AI.** **Google to invest $120 million in AI education programs** SAN FRANCISCO, Jan 25 - Alphabet’s (GOOGL.O), opens new tab Google, already facing an unprecedented regulatory onslaught, is looking to shape public perception and policies on artificial intelligence ahead of a global wave of AI regulation. **A key priority**, one executive told Reuters, comes in **building** out **educational programs to train the workforce on AI.** “Getting more people and organizations, including governments, familiar with AI and using AI tools, makes for better AI policy and opens up new opportunities – it's a virtuous cycle,” said Kent Walker, Alphabet's president of global affairs.

**[1] Ai costs decrease in the long term**

Parry 23 --- (Greg Parry, 3-28-2023, "Artificial intelligence (AI) in Education", https://www.gsineducation.com/blog/artificial-intelligence-ai-in-education) //doa2-24-2025 + master chen 💆in the library

Artificial intelligence (AI) and Personalised Learning

One significant benefit of using AI in education is the ability to personalize learning. AI-driven tools, such as ChatGPT, can analyze students’ data and provide them with personalized recommendations based on their learning styles and abilities. This helps teachers to provide targeted support to individual students, ultimately leading to better learning outcomes. Furthermore, AI tools can help to reduce the burden on teachers by automating routine tasks such as grading, freeing up their time to focus on teaching and providing feedback to students. The Cost Savings of Artificial intelligence (AI) in Education Another significant **benefit** of **AI** in education is **cost savings.** According to a forecast released by technology research firm IDC, worldwide business spending on AI is expected to hit $50 billion this year and $110 billion annually by 2024. While the initial investment in AI may be high, it can **save schools money in the long run by reducing administrative costs and improving efficiency**

**[1b] statistically,**

**Muller 24** --- (Chris Muller, [writer @ Forbes], 10-3-2024, "AI On Campus: What It Means For Your College Investment", https://www.forbes.com/sites/chrismuller/2024/10/03/ai-on-campus-what-it-means-for-your-college-investment/) //doa2-24-2025 + master chen 💆

You've heard me say this plenty of times before – but the landscape of higher education is rapidly evolving, and now even more so, with artificial intelligence (AI) at the forefront of this transformation. As a parent or prospective student weighing the significant investment in a college degree, you might be wondering how AI is changing the college experience, and what it means for your financial future. Recent data shared by Allie K. Miller, a prominent voice in the AI world, has shed light on how quickly **AI tools** are being adopted across **top universities**. And before you say it, this trend isn't just a tech fad - it's actually beginning to reshape how students learn, research, and prepare for their careers. The AI Adoption Race on Campus According to Miller's analysis of data from Perplexity, an AI-powered search engine, several prestigious universities are leading the charge in AI adoption: PROMOTED Massachusetts Institute of Technology (MIT): 11.62% adoption rate Harvard University: 11.53% adoption rate Princeton University: 10.79% adoption rate Other notable universities like Stanford (6.14%), Carnegie Mellon (6.38%), and Columbia (5.78%) aren't far behind. Miller's findings provide a snapshot of how quickly AI is already infiltrating the top educational institutions. The Financial Implications of AI-Forward Universities 1. Enhanced Learning Experience MORE FROM FORBES ADVISOR Graphic Best High-Yield Savings Accounts Of 2024 Best High-Yield Savings Accounts Of 2024 By Kevin Payne, Contributor Graphic Best 5% Interest Savings Accounts of 2024 Best 5% Interest Savings Accounts of 2024 By Cassidy Horton, Contributor Universities investing in AI tools are providing students with cutting-edge resources that can streamline research, offer personalized learning experiences, and simulate real-world scenarios. One example I have been testing is Google's NotebookLM – which allows you to turn any type of document (PDF, text, video, etc.) into a very realistic podcast (among other types of "study materials"). It's easy to see why students are leveraging these types of tools to help them **learn better, faster, and more efficiently.** Investing Digest: Know what's moving the financial markets and what smart money is buying with Forbes Investing Digest. Email address Sign Up By signing up, you agree to receive this newsletter, other updates about Forbes and its affiliates’ offerings, our Terms of Service (including resolving disputes on an individual basis via arbitration), and you acknowledge our Privacy Statement. Forbes is protected by reCAPTCHA, and the Google Privacy Policy and Terms of Service apply. In addition, a meta-analysis by VanLehn, published in the Educational Psychologist, found that intelligent tutoring systems—**AI-**enhanced adaptive learning tools—can significantly improve student performance, with **effectiveness comparable to one-on-one human tutoring**. The video player is currently playing an ad. 2. Future-Proofing Your Degree As AI continues to reshape industries, familiarity with these tools becomes increasingly valuable. The World Economic Forum's Future of Jobs Report 2023 predicted that, by 2027, 69% of companies expect to adopt AI and big data analytics. Graduating from an AI-forward institution could give you a serious competitive edge in this evolving job market. 3. Potential for Cost Savings While the initial investment in AI technology might be high for universities, it could lead to long-term cost savings. In fact, one McKinsey Global Institute report suggests that **AI** could help **reduce** administrative **costs** in higher education **by** up to **30% through automation of routine tasks.** 4. New Financial Aid Opportunities As universities compete to stay on the cutting edge, we might begin to see new scholarships and grants aimed at students pursuing AI-related studies. The National Science Foundation's ongoing initiatives in artificial intelligence research and education have committed substantial funding to support these efforts, for example.

## 2AC---AT: Internet

National Center for Education Statistics xx — (null null [], xx-xx-xxxx, "COE", No Publication, https://nces.ed.gov/programs/coe/indicator/cch/home-internet-access, accessed 3-28-2025) //FK

In 2021, some **97 percent of 3- to 18-year-olds had home internet access,** according to the American Community Survey (ACS). Specifically, 93 percent had access through a computer,1 and 4 percent relied on a smartphone for home internet access.2 The remaining 3 percent had no internet access at home. When compared with the percentage with home internet access overall, there was more variation by race/ethnicity, parental education, and household income in the percentage of 3- to 18-year-olds who had access to the internet through a computer.

## 2AC---AT: Hallucinations

There is innovation

Henshall 23 --- (Will Henshall, [*Will Henshall is an editorial fellow @ TIME. He covers tech, with a focus on AI.*], 11-6-2023, "4 Charts That Show Why AI Progress Is Unlikely to Slow Down", https://time.com/6300942/ai-progress-charts/) //doa2-21-2025 + master chen 💆

in the last ten years, AI systems have developed at rapid speed. From the breakthrough of besting a legendary player at the complex game Go in 2016, AI is now able to recognize images and speech better than humans, and pass tests including business school exams and Amazon coding interview questions. Last week, during a U.S. Senate Judiciary Committee hearing about regulating AI, Senator Richard Blumenthal of Connecticut described the reaction of his constituents to recent advances in AI. “The word that has been used repeatedly is scary.” The Subcommittee on Privacy, Technology, and the Law overseeing the meeting heard testimonies from three expert witnesses, who stressed the pace of progress in AI. One of those witnesses, Dario Amodei, CEO of prominent AI company Anthropic, said that “the single most important thing to understand about AI is how fast it is moving.” It’s often thought that scientific and technological progress is fundamentally unpredictable, and is driven by flashes of insight that are clearer in hindsight. But progress in the capabilities of AI systems is predictably driven by progress in three inputs—compute, data, and algorithms. Much of the progress of the last 70 years has been a result of researchers training their AI systems using greater computational processing power, often referred to as “compute”, feeding the systems more data, or coming up with algorithmic hacks that effectively decrease the amount of compute or data needed to get the same results. Understanding how these three factors have driven AI progress in the past is key to understanding why most people working in AI **don’t expect progress to slow down any time soon.** Level up with ease Paid Content Level up with ease By GODDESS OF VICTORY: NIKKE Read more: The AI Arms Race Is Changing Everything Compute The first artificial neural network, Perceptron Mark I, was developed in 1957 and could learn to tell whether a card was marked on the left side or the right. It had 1,000 artificial neurons, and training it required around 700,000 operations. More than 65 years later, OpenAI released the large language model GPT-4. Training GPT-4 required an estimated 21 septillion operations. Increasing computation allows AI systems to ingest greater amounts of data, meaning the system has more examples to learn from. More computation also allows the system to model the relationship between the variables in the data in greater detail, meaning it can draw more accurate and nuanced conclusions from the examples it is shown. More From TIME Since 1965, Moore’s law—the observation that the number of transistors in an integrated circuit doubles about every two years—has meant the price of compute has been steadily decreasing. While this did mean that the amount of compute used to train AI systems increased, researchers were more focused on developing new techniques for building AI systems rather than focusing on how much compute was used to train those systems, according to Jaime Sevilla, director of Epoch, a research organization. This changed around 2010, says Sevilla. “**People realized that if you were to train bigger models, you will actually not get diminishing returns,**” which was the commonly held view at the time. Since then, developers have been spending increasingly large amounts of money to train larger scale models. Training AI systems requires expensive specialized chips. AI developers either build their own computing infrastructure, or pay cloud computing providers for access to theirs. Sam Altman, CEO of OpenAI, has said that GPT-4 cost over $100 million to train. This increased spending, combined with the continued decreases in the cost of the increases in compute resulting from Moore’s Law, has led to AI models being trained on huge amounts of compute. OpenAI and Anthropic, two of the leading AI companies, have each raised billions from investors to pay for the compute they use to train AI systems, and each has partnerships with tech giants that have deep pockets—OpenAI with Microsoft and Anthropic with Google. Data AI systems work by building models of the relationships between variables in their training data—whether it’s how likely the word “home” is to appear next to the word “run,” or patterns in how gene sequence relates to protein folding, the process by which a protein takes its 3D form, which then defines its function. In general, a larger number of data points means that AI systems have more information with which to build an accurate model of the relationship between the variables in the data, which improves performance. For example, a language model that is fed more text will have a greater number of examples of sentences in which the “run” follows “home”—in sentences that describe baseball games or emphatic success, this sequence of words is more likely. The original research paper about Perceptron Mark I says that it was trained on just six data points. By comparison, LlaMa, a large language model developed by researchers at Meta and released in 2023, was trained on around one billion data points—a more than 160-million fold increase from Perceptron Mark 1. In the case of LlaMa, the data points was text collected from a range of sources, including 67% from Common Crawl data (Common Crawl is a non-profit that scrapes the internet and makes the data collected freely available), 4.5% from GitHub (an internet service used by software developers), and 4.5% from Wikipedia. Algorithms Algorithms—sets of rules or instructions that define a sequence of operations to be carried out— determine how exactly AI systems use computational horsepower to model the relationships between variables in the data they are given. In addition to simply training AI systems on greater amounts of data using increasing amounts of compute, AI developers have been finding ways to get more from less. Research from Epoch found that “**every nine months, the introduction of better algorithms contributes the equivalent of a doubling of computation budget**s.” The next phase of AI progress

Which is why,

Nielsen 25 --- (Jakob Nielsen, 2-13-2025, "AI Hallucinations on the Decline", https://www.uxtigers.com/post/ai-hallucinations) //doa3-27-2025 + master chen 💆

(By the way, using both tools for this article confirmed my previous analysis that OpenAI’s Deep Research is currently more useful than Google’s. Of course, with the pace of AI advances, this conclusion could easily change.)

Bigger AI Models Hallucinate Less

As AI gets more powerful with each generation, hallucinations are on the **decline**. The same study that found 40% made-up literature references in output from ChatGPT 3.5 (from 2022) found only 29% false references from ChatGPT 4, released half a year later.

The Hugging Face Hallucinations Leaderboard has subjected 102 AI models to the same hallucination benchmark, making comparisons possible. The following chart shows the hallucination rate for the 72 models for which I could find the release date.

Each dot indicates the hallucination rate of one AI model according to the HHEM-2.1 hallucination detection model. (Data from the Hugging Face Hallucination Leaderboard.)

The regression line shows that hallucination rates decline by **3 percentage points per year.** If we project the regression line into the future, **it “predicts” that AI will hit zero hallucinations in February 2027,** which coincidentally is when I expect next-generation AI to reach the much-hyped “AGI” (artificial general intelligence).

Obviously, a regression line is not a true predictor of the future, particularly for a dataset like this, with large variability in the underlying data. However, I do expect the next-generation models that we’ll likely get in 2027 to exhibit a very low hallucination rate.