**We Affirm**

## **C1) Scholarship**

#### **Gen AI’s 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.”

#### **Universities uniquely create innovations and economic growth that model globally---that resolves existential risks.**

**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.**

**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.

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

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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

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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**.

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“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

#### **It facilitates 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).

#### **Sustainable development solves extinction---failure causes cascading risks that cumulatively outweigh any single risk.**

Tom **Cernev 20**, 1/xx/2020, Researcher at CSER with degrees in Mechanical Engineering and Theoretical Physics from the University of Adelaide, and a Masters in Engineering from the University of Cambridge, DOA: 3/06/2025,

The importance of achieving foundational Sustainable Development Goals in reducing global risk, https://www.sciencedirect.com/science/article/abs/pii/S0016328719303544)// JZ

The **W**orld **E**conomic **F**orums’ Global Risks Report for 2018 **shows** the **top five global risks in** terms of **likelihood and impact** have **changed** from being economic and social in 2008 **to environmental and technological** in 2018, and are **closely aligned with many SDGs** (World Economic Forum, 2018). The report notes “that **we are much less competent** when it comes to **dealing with complex risks in systems characterised by feedback loops, tipping points and opaque cause-and-effect relationships that** can **make intervention problematic”.** The most likely risks expected to have the greatest impact currently include extreme weather events natural disasters, cyber attacks, data fraud or theft, failure of climate change mitigation and water crises.

These are represented in Fig. 3 by the following exogenous variables. “Climate change” drives the need for Climate Action (SDG 13), “Cyber threat” may adversely impact technology implementation and advancement which will disrupt Sustainable Cities and Communities (SDG 11); Decent Work and Economic Growth (SDG 8) and the rate of introduction of Affordable and Clean Energy (SDG 7), with reductions in these goals having direct consequences in also reducing progress in the other goals which they are closely linked to. “Data Fraud or Threat” has the capacity to inhibit innovation and Industrial Performance (SDG 9), reducing competitiveness (and having the potential to erode societal confidence in governance processes). “Water Crises” (linked with climate change) have a direct impact on Human Health and Well Being (SDG 3) as well as reducing access to Clean Water and Sanitation (SDG 6) and reducing agricultural production which increases Hunger (SDG 2). The causal loop diagram also highlights “Conflict” as a variable (driven by multiple environmental-socio-economic factors) which together with regions most impacted by climate degradation will lead to an increase in migrant refugees enhancing the spread of disease and global pandemic risk, thus impacting directly on Human Health and Well Being (SDG 3)

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, Farquhar, Halstead, Schubert, & Snyder-Beattie, 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, Inayatullah, Burgman, Sutherland, & Wintle, 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.

#### **Fast growth halts existential threats.**

**Roubini ’22** [Nouriel Roubini; Professor Emeritus, Stern School of Business, New York University, Ph.D., International Economics, Harvard University. Nouriel Roubini, 2022, “Chapter 12: A More “Utopian” Future?” and “Epilogue,” in Megathreats: Ten Dangerous Trends That Imperil Our Future, and How to **Survive Them, Hatchette Books, University of Kansas Libraries, https://avalonlibrary.net/ebooks/Nouriel%20Roubini%20-%20Megathreats%20(2022).pdf] mac**

Many of the problems fueling **megathreats require solutions based on high-powered economic growth. High growth**—let’s say, between 5 and 6 percent **GDP sustained over time** in advanced economies—**can help pay down the debts** that threaten us. That kind of growth **generates resources that** can help us **tackle expensive public projects to forestall climate change, aging, and tech unemployment, or** tackle **future pandemics. It reduces political tensions and strife**. Higher growth is driven to a great extent by technological innovations that increase productivity. Could tech innovation help us grow our way out of our troubles?

Breakthroughs on climate change could deliver cascading benefits. Better health boosts economies. **Strong growth attacks wealth inequality if it creates more jobs and makes a larger welfare system** (progressive taxes and public spending and possibly UBI) more palatable for all. Scientific research and innovation reduce costs and **increase output in goods and services, a recipe for robust income generation** and wealth creation. Think, for instance, about a world where clean fusion produces all the energy needed and costs less than fossil fuels or current sources of renewable energy. Cheap energy **would slash the** current stratospheric **costs of desalinization**. Besides quenching thirst, plentiful **fresh water would expand food production** and lower its cost. And innovations in **farming technologies**—like vertical farming or lab-grown meat—may **lessen the need to use lots of water and polluting fertilizers** in food production and reduce the reliance on livestock farming that is the source of up to 25 percent of greenhouse gas emissions.

**High economic growth would ease many debt problems** afflicting the global economy. **The sustainability of debts**, whether private or public, explicit or implicit, domestic or foreign, household or corporate, **hinges on the borrower’s income**. If income growth can outpace increases in debt, many **debts** that are **currently on an unsustainable path would become manageable. Strong growth supplies the best solution**. Technology that accelerates growth at a rapid pace is a key ally.

**A rejuvenated Western system would counteract calls for deglobalization and protectionism. Sluggish growth and inequality spur populism, and populism stirs** economic **nationalism. Strong**, inclusive, and sustainable **growth keeps both** trends **in check**. Greater global **economic integration spreads tech innovations that invigorate global commerce. Cooperation begets wider cooperation**. Some decoupling between the United States and China might occur **in a more connected world**, but **adversaries with deeper mutual interests may look more skeptically on radical decoupling and military confrontation**. The United States and China have ample reasons to collaborate. For both, **survival depends on coping with** climate change, **pandemics, inequality, supply chain integrity**, and, of course, boom-and-bust cycles. Their rivalry would continue, but in addition to some containment and confrontation there would be ample room for cooperation and healthy competition.

**Technological innovations could facilitate robust global trade** in services, data, information, and technology. Geopolitical sensibilities preclude trade without any restraints, but a prodigious stream of new technologies could demolish many hurdles. **Revitalized trade in digital goods and services would reinforce global and regional economic ties.** The eurozone would welcome risk sharing and lower its risk of breaking up. In this scenario, the world retains the dollar as its reserve currency, eventually in the form of a central bank digital currency—an e-dollar.

What if the last seventy-five years has been the exception rather than the rule? **What if the last three-quarters** of a century **has lulled us into believing** that **the next** few **decades will continue** on the same path? What if **we have forgotten the lessons of** history from a century ago? In the first four decades of the twentieth century, we faced **World War** I, then **the** deadly **Spanish flu** of 1918–19, then **deglobalization** and bouts of hyperinflation, and then the Great Depression. That brought massive **trade wars**, financial and **debt crises, and** deflation; then **the rise of populist, authoritarian, and** militarily **aggressive regimes** (Nazism in Germany, Fascism in Italy and Spain, militarism in Japan). That, in turn, eventually led to World War II and the Holocaust.

The patterns of a century ago may be a harbinger of what we are facing now. In many ways, **the megathreats of today are worse than** the threats of **a century ago**. Our financial system is more leveraged, our **inequality is greater, our weapons are much more dangerous. Populist politicians** have more ways of reaching and manipulating vast audiences. And of course, climate change is vastly more accelerated now than it was then. Even **the risk of nuclear conflict has reemerged. Cold War II may yet lead to hot wars**.

## **C2) Financial Education**

### **Unq: Opportunities for free financial education are limited**

**Ross 22** [Ross, Jenna, 5-17-2022, “Mapped: Personal Finance Education Requirements, by State,” Visual Capitalist, https://www.visualcapitalist.com/students-receiving-personal-finance-education-by-state/, accessed 2-20-2025] // CW

**When you graduated from high school, did you know how to create a budget? Did you have an understanding of what stocks and bonds were?** Did you know how to do your own taxes? **For many Americans, the answer to these questions is probably a “no”. Only 22**.7**% of U.S. high school students are guaranteed to receive a personal finance education.** While this is up from 16.4% in 2018, this still represents a small fraction of students. This graphic uses data from Next Gen Personal Finance (NGPF) to show the percentage of high school students required to take a personal finance course by state.

### **Link: AI tools can help provide easier processes and free financial counseling**

**Golston 24** [Golston, Allan (President, U.S. Program, Gates Foundation), 12-17-2024, “Unleashing AI’s Potential for Equitable Academic Outcomes and Economic Opportunity,” U.S. Program, https://usprogram.gatesfoundation.org/news-and-insights/articles/unleashing-ais-potential-for-equitable-academic-outcomes-and-economic-opportunity, accessed 2-20-2025] // CW

Economic mobility is a very long-term goal, but there are supports that people need right now to achieve financial stability while climbing the economic ladder. Our partner, Propel, uses technology to help millions of families meet basic needs by navigating complicated government systems and accessing safety net benefits like the Supplemental Nutrition Assistance Program (SNAP). Propel’s **AI**-powered mobile app **streamlines processes for eligible recipients, securely connects them to their** Electronic Benefit Transfer (**EBT**) **accounts – alleviating the need to collect and track paper receipts** – and provides information and answers to their questions about the program. Beyond helping people navigate complicated systems, AI also helps those experiencing poverty improve their financial health. For instance, it’s estimated that 3.8 million people in our focus population experience bankruptcy and wage garnishment, over 16 million of them struggle with unmanageable debt and more than 26 million lack access to credit. We’re working with Upsolve to expand its **AI-powered financial counseling tools** to **provide free, personalized recommendations on debt management, credit improvement, and access to critical financial resources for individuals.** **To date, this tech**nology **has helped thousands** of people **eliminate over $600 million in debt.**

### **The Impact is Poverty: Increasing financial literacy reduces the likelihood of poverty**

**Lang et al 24** [Lang, Ngoc Duc, Tran, Ha Mai, Nguyen, Giang Tra, and Vo, Duc Hong, 08-07-2024, “An Untapped Instrument in the Fight Against Poverty: The Impacts of Financial Literacy on Poverty Worldwide,” Social Indicators Research, https://link.springer.com/article/10.1007/s11205-024-03404-w, accessed 2-20-2025] // CW

The estimated coefficients of financial literacy are shown in Table 2. Columns 1 and 2 show the empirical results from probit models. Socio-demographic factors (i.e., age, education, employment status, and others) are incorporated as control variables in all models. Furthermore, the country where respondents live can affect economic opportunities, access to education, and the availability of financial resources, which consequently affect poverty. Hence, country dummies are added to control variations across countries. Column 1 shows that financial literacy negatively affects the probability of falling into poverty. The slope coefficient of financial literacy is statistically significant at the 1 percent level. Holding other things constant, **a unit increase in the financial literacy index corresponds to a 6.2% decrease in the probability of falling into poverty.** This coefficient even increases from 6.2 to 7.5% after controlling variations across countries (Column 2). Overall, the results indicate that **financial literacy is negatively associated with the probability of falling into poverty,** supporting Hypothesis 1.

### **Vote on poverty– it kills.**

**Wilkinson ND** [Mark R. Rank, the Herbert S. Hadley Professor of Social Welfare at Washington University in St. Louis., no date available, “Why is it important to reduce poverty?” Confront Poverty, Module 9, https://confrontingpoverty.org/poverty-discussion-guide/can-we-estimate-the-overall-costs-of-poverty/, accessed 3-28-2025] // CW

**Why is it important to reduce poverty?**

This is a vital question to address, and one that is often ignored. Obviously poverty exacts a heavy toll upon those who fall within its grasp. For example, one of the most consistent findings in epidemiology is that the **quality of** an individual’s **health is negatively affected by** lower socioeconomic status, particularly impoverishment. **Poverty** is **associated with a host of health risks, including** elevated rates of **heart disease, diabetes,** hypertension, **cancer, infant mortality, mental illness**, undernutrition, lead poisoning, asthma, **and dental problems**.

Shorter Life Expectancy

**The result is a death rate** for the poverty-stricken between the ages of 25 and 64 that is approximately **three times higher** than that for the affluent within the same age range, **and a life expectancy** that is **considerably shorter.** For example, Americans in **the top 5 percent** of the income distribution can expect to **live** approximately **9 years longer** than those in the bottom 10 percent. As health expert Nancy Leidenfrost writes in her review of the literature, “Health disparities between the poor and those with higher incomes are almost universal for all dimensions of health.”

However, what we have failed to **recognize** is that poverty also places enormous **economic, social,** and psychological **costs on the nonpoor as well**. These costs affect us both individually and as a nation, although we have been slow to recognize them. Too often the attitude has been, “I don’t see how I’m affected, so why worry about it?”

Poverty Affects Us All

Yet the issues that many Americans are in fact deeply concerned about, such as crime, access to and affordability of health care, race relations, and worker productivity, to name but a few, are directly affected and exacerbated by the condition of poverty. As a result, the general public winds up paying a heavy price for allowing poverty to walk in our midst. A report by the Children’s Defense Fund on the costs of childhood poverty makes this strikingly clear,

The children who suffer poverty’s effects are not its only victims. When children do not succeed as adults, all of society pays the price: **businesses** are able to **find fewer** good **workers**, consumers pay more for their goods, **hospitals** and health insurers **spend more treating preventable illnesses**, teachers spend more time on remediation and special education, private citizens feel less safe on the streets, governors hire more prison guards, mayors must pay to shelter homeless families, judges must hear more criminal, domestic, and other cases, taxpayers pay for problems that could have been prevented, fire and **medical workers** must **respond to emergencies that never should have happened, and funeral directors must bury children who never should have died.**

When we speak of homeland security, these are the issues that truly undermine us and our security as a nation.

Quantifying the Costs

There have been several attempts to quantify the cost of poverty in terms of a monetary amount. However, the ability to estimate the magnitude of the costs surrounding an issue such as poverty is exceedingly complex. Nevertheless, in a recent study by Michael McLaughlin and Mark Rank, the researchers estimated the expense of childhood poverty with respect to increased health care costs, criminal justice costs, and costs associated with reduced productivity and economic output. McLaughlin and Rank calculated that **the** overall economic **price tag of childhood poverty in the U.S. totaled** approximately **1 trillion dollars a year, or 28 percent of the entire federal budget** in 2015.

Suffice it to say that poverty exacts a high toll upon both the poor and the nonpoor in our country. In your thinking and discussions of poverty, what are some of the other reasons that may be important for reducing poverty? One line of thinking is to explore and consider the concepts of social justice and fairness with respect to poverty. Is the condition of poverty just? Why or why not? What about childhood poverty or poverty amongst the elderly? Is impoverishment among these groups fair? Should Americans who work full-time still be mired in poverty? Why or why not? There are many approaches to thinking about why reducing poverty is important.

**2NC**

#### **Answer: Downsides are irrelevant or self-corrected.**

**Li ’23** [Zhicheng; Researcher from Programme of Applied Psychology, School of Humanities and Social Science, The Chinese University of Hong Kong, Shenzhen, Guangdong 518172, People's Republic of China; August 2023; "Why and how to embrace AI such as ChatGPT in your academic life," PubMed Central (PMC); https://pmc.ncbi.nlm.nih.gov/articles/PMC10445029/ DOA: 2-12-2025] sumzom + mac

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.

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

**Herman ’24** [Eti; CIBER Researcher, 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

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 canbe **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 ofconducting 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 comeup 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 scratchor 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.

#### **Answer: This fear of teachers being replaced by AI has been stoked time and time again.**

**Elliott, David. “'Education is a place where we build democracy'. Why a teacher's unionisn't afraid AI will replace teachers.” World Economic Forum, July 2, 2024,https://www.weforum.org/stories/2024/07/artificial-intelligence-education-teachers-union/. Accessed February 14, 2025.**

**Edwards says many teachers are optimistic about the possibilities these tools bring.He cites examples, such as special education teachers using accessible digital textbooks, which allow diverse learners, including those with disabilities, to listen to or interact with the text in different ways. Language teachers he speaks to, he**

**continues, are “really excited” about being able to provide support in multiplelanguages.In his view, teachers are always early adopters who find ways to bring new technologies into the classroom to enhance learning. “We had it with the radio. ‘Theradio will make teachers obsolete’.” Then teachers incorporated radio programmesinto their classrooms, he says, and the class discussed their thoughts afterwards.“Then they moved on to the VCR tape ... ‘Now we can just have one teacher tape alesson and then everyone can play that lesson’. Of course, that didn’t happen either.“The experience of education is more than just the delivery of content. It’s relational,it’s not transactional. And that’s what I am seeing happening right now with AI.”**

East JS Responses:

Their Moquin evidence is power-tagged– the tag makes the claim that educational tools are currently cheaper than AI, but there’s no comparison within the evidence that gen AI is more expensive.

Their Dhruv evidence states AI as expensive as $120K, but do the control-F test– *nowhere* is education mentioned. The evidence describes the costs to build an AI, not to use one in a school.