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Opinion

Artificial Intelligence Alone Will Not Democratise Education: On Educational Inequality, Techno-Solutionism and Inclusive Tools

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Abstract: Artificial Intelligence (AI) in Education claims to have the potential for building personalised curricula, as well as bringing opportunities for democratising education and creating a renaissance of new ways of teaching and learning. Millions of students are starting to benefit from the use of these technologies, but millions more around the world are not, due to the digital divide and deep pre-existing social and educational inequalities. If this trend continues, the first large-scale delivery of AI in Education could lead to greater educational inequality, along with a global misallocation of educational resources motivated by the current techno-solutionist narrative, which proposes technological solutions as a quick and flawless way to solve complex real-world problems. This work focuses on posing questions about the future of AI in Education, intending to initiate the pressing conversation that could set the right foundations (e.g., inclusion and diversity) for a new generation of education that is permeated with AI technology. The main goal of our opinion piece is to conceptualise a sustainable, large-scale and inclusive AI for the education ecosystem that facilitates equitable, high-quality lifelong learning opportunities for all. The contribution starts by synthesising how AI might change how we learn and teach, focusing on the case of personalised learning companions and assistive technology for disability. Then, we move on to discuss some socio-technical features that will be crucial to avoiding the perils of these AI systems worldwide (and perhaps ensuring their success by leveraging more inclusive education). This work also discusses the potential of using AI together with free, participatory and democratic resources, such as Wikipedia, Open Educational Resources and open-source tools. We emphasise the need for collectively designing human-centred, transparent, interactive and collaborative AI-based algorithms that empower and give complete agency to stakeholders, as well as supporting new emerging pedagogies. Finally, we ask what it would take for this educational revolution to provide egalitarian and empowering access to education that transcends any political, cultural, language, geographical and learning-ability barriers, so that educational systems can be responsive to all learners' needs.

Keywords: open education; recommendation systems; Wikipedia; lifelong e-learning; state-based learner modelling; Sustainable Development Goal 4

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1. Introduction

Education is a human right that has been recognised by the International Covenant on Economic, Social and Cultural Rights among several other international conventions. Access to education benefits individuals and societies alike and goes hand in hand with social inclusion, economic growth, poverty reduction and equality. A strong educational system can broaden access to opportunities, improve health, bolster the resilience of communities and institutions, drive long-term economic growth, reduce poverty and spur innovation [1]. Education could also bring a fundamental shift in how we think, act and relate to our responsibilities toward one another and the planet, helping to nurture a new generation that supports the transition to a prosperous and sustainable social and environmentally friendly future. In this sense, we are all stakeholders in educational systems. Firstly, because we are all learners, but also because of the global benefits that an empowering and strong educational system could bring. We use the term "stakeholders" in this context and argue that stakeholders of education go beyond learners and teachers and include administrators, policymakers, parents and other groups that play a role in this complex system as well as benefit from it. In the context of leveraging Artificial Intelligence (AI) and Machine Learning (ML) in Education, data scientists, computer scientists and developers who contribute to the ecosystem also become critical stakeholders [2]. A very small elite has benefited from the luxury of access to education until recently, and this was also a result of development that spanned over several generations. Before that, the chances of any child getting the most basic education were very slim, no matter where they were born [3].

However, while access to education has significantly increased around the world in the last decade, exclusion in education is still persistent. According to UNESCO Institute of Statistics data for the school year ending in 2018, an estimated 260 million children worldwide did not have access to school education, and social inequality was a major reason for this [4]. The total includes 59 million children of primary school age, 62 million of lower secondary school age and 138 million of upper secondary school age. At present, an estimated 759 million adults are still illiterate and do not have the awareness necessary to improve both their living conditions and those of their children. Identity, background and ability dictate these education opportunities. Particularly, the World Inequality Database on Education (WIDE) [5] highlights the powerful influence of circumstances, such as wealth, gender, ethnicity and location, which play an important role in shaping opportunities for education and life. According to this report, only 18 of the poorest youth complete secondary education for every 100 of the richest in all countries except for North America and high-income European countries. Hardly any young women coming from a poor rural background complete secondary school in at least 20 countries, including many from sub-Saharan Africa. During the pandemic, these inequalities have deepened. Specifically, 40% of countries worldwide have not supported learners at risk during the crisis [4].

1.1. Paper Overview

The opinion paper starts with an introduction where the reinforcement of exclusion through AI is pointed out (Section 1.2), followed by the motivation inspired by this effect (Section 1.3), concluding by describing the role that Educational Technology and AI can play in the democratisation of education (Section 1.4). The promise and the peril of AI in Education are described next (Section 2). Then, the four pillars are identified and proposed (Section 3), with each pillar being further elaborated in a separate subsection. Based on the background presented in Sections 2 and 3, the conclusions are presented in Section 4.

1.2. Exclusion in Education Is Still Persistent

Educational systems are still leaving one in four 15-year-old students globally to report feeling like outsiders at school [4]. Language is one of the barriers, with this number rising to above 30% in the Dominican Republic, one of the most linguistically diverse regions in the world but where educational systems do not always account for this. Diversity is also not sufficiently reflected in our educational systems [4]. Many countries still practice segregation in their educational systems. In the case of students with disabilities, laws in 25% of countries (but over 40% in Asia, Latin America and the Caribbean) make provisions for education in separate settings. Additionally, in OECD countries, more than two-thirds of all immigrant students attend schools where at least half the students are immigrants. In countries like Brazil, Mexico and Peru, there is also persistent inequality by indigenous background, even after controlling for social class.

Citing UNESCO's Global Education Report in 2020 [4], "*Debating the benefits of inclusive education is akin to debating the benefits of human rights. Inclusion is a prerequisite for sustainable* *societies. It is a prerequisite for education in, and for, a democracy based on fairness, justice and equity. It provides a systematic framework for removing barriers according to the principle that 'every learner matters and matters equally'*". The benefits of inclusive education for those left behind are hard to quantify, as they extend over generations. These include improvement in academic achievement, social and emotional development, self-esteem and peer acceptance, as well as preventing stigma, stereotyping, discrimination and alienation.

More attention needs to be given to determining effective ways to prepare teachers for work in inclusive settings and providing them with support tools. For example, the 2018 Teaching and Learning International Survey reported the need for training in teaching students with special needs. Recent data using the Child Functioning Module (in 14 countries) suggest that children with disabilities face complex barriers and constitute 15% of the out-of-school population. Specifically, those with a sensory, physical or intellectual disability are 2.5 times less likely to have been in school in comparison to their peers without disabilities, possibly due to lack of adapted infrastructure and materials and because of the known link between disability and poverty [4]. In this sense, assistive technology can determine participation or marginalisation. Such technologies improve self-esteem, optimism and graduation rates but are often unavailable due to lack of resources or not used effectively due to various challenges associated with the appropriate adoption of technology. These include teachers' knowledge and confidence in using technology, product quality and reliability; potential workload considerations; teacher ownership and trust; schools' support mechanisms for help to teachers; and potential privacy and ethical concerns of teachers [6].

There is also a chronic lack of quality data on those left behind [4]. Figures on learning are often taken from school even if many often marginalised students are not participating. Data on and for inclusion (across languages, cultures, subject domains, geographic/virtual sites and disabilities [7]) in education are essential. The gaps in opportunities for education and their correlation to outcomes among learner groups can be identified by looking at data on inclusion. Such data allow for identifying those who may get significantly disadvantaged while observing the severity of the barriers they face. Inclusion data provide governments with a pathway to develop policies while reinforcing their visibility via continuous data collection rather than relying on less easily observed qualitative outcomes.

1.3. Motivation

As the primary goal, this work identifies several key pillars for building and maintaining a sustainable, large-scale and inclusive AI in the Education ecosystem that facilitates equitable, high-quality lifelong learning opportunities for all. In this spirit, we identify and describe several tools that we argue will prove essential. This is an opinion article based on a critical scoping review of the available evidence and not a systematic literature review. We bring a non-systematic critical overview of the current state of the understanding of this topic. The views presented in this paper are learnings from multiple large-scale research projects run across Europe, such as X5GON [8], HumaneAI [9] and AT2030 [10], and are based on larger discussions we have had with AIEd researchers, as well as our personal views on the challenges arising in the field. Our opinion resonates with the viewpoints of others influential in the field [11]. We re-evaluate the existing research and considerations in light of the major recent developments in the field of AI, e.g., the advancement of generative AI, which are dramatically challenging the status quo of our educational systems and provide opportunities for radical changes. We critically discuss the opportunities and risks that AI could bring to education, in terms of supporting teachers and learners, as well as in enabling a more inclusive educational system. This goal has always been significant, yet rethinking the future of education is all the more important following the COVID-19 pandemic, which further widened educational inequality and put a spotlight on the lack of resilience of our educational systems [4,12]. Post-pandemic retrospectives provide further evidence on how the conventional school systems were severely disrupted in developing nations and how more resilient blended learning approaches (combining face-to-face and online learning seamlessly and in a complementary way) should be sought going forward [13]. Blended learning requires a balance between the self-regulation of learners and teacher-guided instruction approaches, and AI could play a pivotal role in managing this balance.

1.4. Role of AI and Educational Technology

AI is starting to exemplify novel methods of teaching and learning [14] and showing potential in personalising learning [15]. AI in Education (AIEd) [14] covers, among others, intelligent, personalised and conversational educative systems (e.g., systems which provide scoring, assessment, feedback and hints or that match users for collaborative learning) with the aim to support stakeholders and put them in control of the learning process. One of the most ambitious use cases of AIEd, Intelligent Tutoring Systems (ITSs), has been shown to lead to similar learning gains to face-to-face one-on-one instruction in both individual experimental studies [16] and metareviews of the field [17], while personalised learning, in general, can improve the learning gains of an average student by the order of two standard deviations [18]. Despite this immense theoretical potential of personalised technology-enhanced education and a large amount of monetary investment in these learning technologies, such innovations have not delivered many practical results yet [12,19]. Less ambitious AIEd technologies (e.g., support tools for teachers) are, however, slowly starting to play a role in providing support to teachers, students, and the learning process more broadly [20,21]. But, without a doubt, not all are benefiting equally [22].

Taking a systems view, Educational Technology (EdTech) in this context can be scoped as both methods (utilising information technology and digital communication) and media (videos, websites, interactive learning resources, etc.) [23,24]. Historically, technological change has been shown to increase between-country inequality [25]. In more recent studies, similar results are also observed, more specifically in Education regarding the use of Massive Open Online Courses (MOOCs). MOOCs have been brought into educational systems with the goal of democratising education, but emerging evidence indicates that MOOCs do not spread benefits equitably across global regions. Rather, they reflect prevailing educational disparities among nations [26]. Similarly, AIEd could bring risks of exacerbating the wide education and opportunity gap and, at the same time, may have other additional negative consequences globally. It is not by accident that Sustainable Development Goal 4 on education explicitly exhorts countries to ensure inclusive education. Inclusion improves learning for all students. Mechanical solutions that do not address the deeper barriers of exclusion and inequity can only go so far towards improving learning outcomes. Inclusion must be the foundation of approaches to teaching and learning [4].

In line with the motivation outlined in Section 1.3, we argue that inclusion should be at the epicentre of EdTech design. Our work asks and imagines how this AI-based educational potential could benefit everyone equally and support more inclusive educational systems while maintaining scalability and sustainability. In our view, providing high-quality education to almost eight billion people requires more than what current technology-centred solutions can provide alone. We are in urgent need of future-oriented visions of connected social and technological orders. In this paper, we provide some examples of such socio-technical imaginings, more specifically of ways to scale education and make it inclusive. For example, the recent boom of Open Educational Resources (OERs) [27] and MOOCs [28] could mean that the democratisation of more inclusive learning may be within reach. This is because these massive (100,000 s) collections of learning resources [20] can be exploited to improve AI's understanding of knowledge and be used as learning resources that can be effectively discoverable by individuals using AI (via search and recommendation systems [29], scalable quality assessment [30], etc.). However, this reality is feasible only if the objectives of AIEd are adequately aligned and collectively designed, with accessibility, equity, openness and inclusion at their core. In many ways, achieving inclusion is a management challenge. Historically, the human and material resources to address diversity have been concentrated in a few places as a legacy of segregated provision and are unequally distributed. Mechanisms and incentives should be put in place to move resources flexibly, ensuring that specialist expertise supports mainstream schools and non-formal education settings. We believe OERs, which include openness and diversity in their core design, hold great potential in this respect.

This work starts summarising how AI could support learners and teachers at scale, reflecting on some of the social and technical challenges of delivering such support. We then identify some of the barriers to everyone benefitting from decades of advances in AIEd, to start the dialogue to ensure these tools narrow the educational inequity gap rather than increase it. We finally discuss some promising resources that could be used to leverage this participatory educational revolution. Ultimately, our work aims to pose this question: *"What would it take for AI tools to help us democratise education?"*. With this question, we do not mean *"Could AI replace teachers?"*. But rather, among others, we discuss the extent to which *"AI tools could support the role of teachers to be more effective and inclusive, help us surpass language barriers and support learners often left behind"*.

2. AI in Education (AIEd): The Promise and the Peril

Before synthesising solutions, it is sensible to focus on both the positive and negative aspects of AIEd towards democratising education.

2.1. The Promise

AIEd has been under active development for several decades now [31] and has made significant advances on different fronts, especially in areas such as Intelligent Tutoring Systems (ITSs) [32,33], educational recommendations [21], MOOC management [28,34] and taxonomy/prerequisite detection [35], among others. Recent work has also shown that AI could be used to accumulate learning resources at scale [20], as well as enrich these to break language barriers by creating cross-lingual translations/transcriptions [36], domain-/language-agnostic topic annotations [37], and visual and interactive content summaries that support the learner, providing synthetic video materials that are as effective as learning from human teachers' video recordings [38]. Just as educational materials can be better understood and accumulated across cultures, modalities and languages using AI [20], promise lies in leveraging AI to personalise learning materials catering to the needs, disabilities, and specific preferences of learners (e.g., readability, level of language, speaker speed, etc.). For example, AI-powered systems providing automatic adaptation of educational materials by deconstructing learning resources into finer-grained building blocks (e.g., deconstructing a video into audio, transcript and picture frames) are starting to emerge and are starting to play a role in supporting a more diverse population of learners as well as enhancing accessibility [39]. Such systems could unlock levels of personalised adaptation that were previously considered impossible (e.g., simplifying video and audio content and rephrasing). With the advent of large language models (LLMs), several of these use cases have become more practical in the last few years [40]. The generative capabilities of linguistic content (e.g., automatic question generation [41,42], personalised feedback [43] and summarisation [44]) have seen significant progress. There is also recent evidence of human subjects assessing generative outputs augmenting their learning activities as acceptable [45,46]. More recent works even show that relatively smaller language models, which are significantly less expensive to train and deploy, can be equally effective in education-related generative tasks [41,42,47]. These developments pose an enormous opportunity in terms of generating highly personalised learning materials for effective education, taking personalised education in the direction of precision medicine. An extensive review of these opportunities can be found in [48]. However, these models also come with limitations. They can lead to the homogenisation of thinking due to the monolithic nature of the models. There is also the lack of interpretability of LLMs making it difficult to ensure they are faithful. Deployed unchecked, these models can exacerbate misinformation and biases (e.g., gender or race stereotypes) at scale. The ultimate ambition of AIEd would be, however, a lifelong learning companion [7] that understands the strengths and weaknesses of individual learners to present materials and exercises to increase their learning gains while providing prompt feedback when needed. Being able to cooperatively operate across languages, cultures and special needs of individuals would make this companion humane. Above all, this companion should interplay with political and operational constraints, respecting privacy and safety and prioritising the learner's autonomy and agency, moving away from prescriptive AI [49]. Such technology should also allow teachers to use their training and experience to fulfil less mundane tasks such as personal attention, advanced pedagogy, pastoral care and other complex support tasks that preserve equity in the classroom. While being an ambitious and impactful destination (dreamed of since 1972 [19]), achieving sophistication in AIEd systems will take a long time. We believe that by focusing on *augmenting* teacher/stakeholder capabilities, rather than replacing them, AIEd can bear more fruits in the short term. This will also enable us to achieve sustainable, large-scale lifelong educational practice enhanced by AI.

2.2. The Peril (Challenges)

While promising technological advances have been unveiled in the last few years, increasing access to education remains predominantly a political and social issue [22], and the disconnection between technology and the surroundings where it operates leads to consistent failures [50]. AI technologies could help education in different ways, but they are unlikely to offer a solution on their own. To make progress, we have to understand the reasons behind the children's absence from schools [3] and the obstacles learners face in their learning paths. There are many conflict areas in the world with ongoing violence (such as Ukraine, Syria, Yemen, Sudan, and Nigeria) that are major contributors to this barrier. Close to 50% of children who are not pursuing education in the world live in conflict-affected countries [51]. Poverty is the other main barrier that is closely intertwined with conflict and violence, affecting global child education [52]. Poverty drives children to work in the worst-case scenarios, most commonly in farms and other establishments, leading children to give up school early in their lives or not to start school education altogether. Low-income countries can only afford to allocate a small fraction of public finances to education. For example, a high-income country like Austria might allocate an annual education budget that is 200-fold greater compared with that of the Democratic Republic of Congo, a low-income counterpart [3]. For example, while laws on universal free and compulsory basic education have in general helped reduce child labour, in some countries, such as Paraguay and Peru, child labour is still permitted at age 14, before compulsory education finishes [4].

Furthermore, if AIEd technologies are not designed appropriately and collaboratively and are not being deployed with the right infrastructure across nations, one of the greatest perils we could face is for these to exacerbate educational inequality. We think that access through good connectivity to quality scientific content and capacity building to allow skill development using such content are both important parts of providing quality education for all. Nonetheless, these could in themselves have other less desirable consequences on a global scale, such as diverting educational resources that could be put to more effective use and propagating dangerous biases of different natures at scale [53]. Various recent works have highlighted other challenges to circumvent before benefitting from the opportunities of AIEd. For example, IDIA [54] identifies several technical challenges general to AI: availability of quality data, accountability, transparency and addressing biases. Access to these technologies is also about power. After all, in a society that is thoroughly permeated by technology, those who possess access to it can influence processes and will have greater opportunities. The recent UNESCO [22] and IRCAI [7] reports narrow down the challenges in AIEd to scalable content understanding and fact-checking, learner modelling, personalised learning, transparency and scrutiny. These reports also expand on scalable evaluation, which is an essential part of verifying learning [32], and the need for addressing lifelong learning.

Amid the promises of technology-enhanced education, success stories seldom benefit developing nations. To start with, there is a geographical, cultural and language imbalance in terms of open education repositories around the world [55]. Even more, the majority of educational materials that have been accumulated via AI are in popular European languages, due to the narrow selection of translation models that are the current focus in the research community [20]. Even among the available translation models, performance only marginally surpasses the "humanly acceptable" level [56]. This is far from the needed quality for learning purposes, where translation and transcription errors can easily impair the learning experience. While the scientific community maintains enthusiasm in advancing personalised learner models, the ITS solutions that are very specific to narrowly scoped datasets (such as mathematics and programming learning in controlled learning environments nourished in developed countries [35,57,58]) are improved rigorously, yet their generalisability to low-resource settings is extremely limited. The lack of "humanly acceptable" quality is not an issue specific to learner models and datasets. In addition to all these shortcomings of existing research, there is a whole realm of additional considerations such as Internet connectivity, unequal access to digital devices as well as accessibility needs that need to be accommodated when innovating responsibly in this space [13].

There still exist countries that have some distance to catch up in terms of including disabled communities. For example, some countries still do not recognise sign language as an official language, and this represents an important barrier to assistive technologies. Furthermore, 80% of the world's population of people with a disability live in developing countries. With the lack of educational resources, these communities struggle to gain the skills necessary to create a livelihood, contributing to the known link between poverty and disability [4,59]. Assistive technology, with the help of domain clinicians, could help this community, with AI potentially expediting this process [59] (e.g., Google Euphonia, which helps people with non-standard speech to be better understood [60]). In the context of closing the gap for disabled communities with AI, the promise is yet to deliver tangible results. The AI technologies that can help disabled users (such as speech-to-text transcribers, eyeball trackers and handwriting recognisers), though perceived to have reached groundbreaking levels of performance, have not reached the point where they can be deployed to help disabled people at scale. Instead of helping users, they may often frustrate the users and worsen their experiences (e.g., speech recognition software carrying out wrong steps due to transcription error and misspelling phrases) [61]. These scenarios indicate how some AI-enabled tools are pushing the boundaries of ethical obligations in the wrong direction, while the general population is under the impression that hyped AI technologies are empowering these communities more often than they do.

3. Proposed Pillars for Inclusive AIEd

Over the last few decades, one of the objectives of AIEd has been increasing learning gains using personalisation, i.e., building artificial learning companions that can, to a certain extent, replace teachers and guide the learning process alone, often taking a techno-centric approach to the scarcity of human teachers [15,31]. Focusing as a community on this ambitious goal, however, underestimates the central role that teachers play in our educational ecosystems today and does not address the wide range of challenges that teachers and learners around the world currently face. Some of such global challenges are related to inclusion, diversity and scalability in learning. In this section, we discuss our views on pillars for the AIEd community that could support the challenges presented above. Our proposed pillars in this section connect to previous recommendations aimed at addressing inclusion in education. Specifically, we point to the report *"All means all"* [4], which set key recommendations to help countries achieve the 2030 inclusive education targets:

- *Target financing to those left behind:* There is no inclusion while millions do not have access to education. We argue for making access to education one of the main foci of AIEd research and innovation.

- *Share expertise and resources:* It is the only way to sustain a transition to inclusion. We propose relying on open educational materials and open-source tools.
- *Engage in meaningful consultation with communities and parents:* Inclusion cannot be enforced with a top-down approach. We propose participatory tools as a core pillar of AIEd research and innovation.
- *Apply universal design:* Ensure inclusive systems fulfil every learner's potential. We propose AI tools that are modality- and language-agnostic, aiming to adapt to the learners' needs.
- *Prepare, empower and motivate the education workforce:* All teachers should be prepared to teach all students. Assistive technologies can play a key role in this regard if they are designed and developed in the right way.
- *Collect data on and for inclusion with attention and respect:* Avoid stigmatised labelling. A human-centric approach to AIEd is needed.
- *Learn from peers:* A shift to inclusion is not easy. For this, we propose creating education ecosystems where everyone can contribute, independently of language or ability. Language and translation models, OERs and open-knowledge bases like Wikipedia are key in this regard.

With our objective of building and maintaining a sustainable, large-scale and inclusive AIEd ecosystem that facilitates equitable, high-quality lifelong learning opportunities for all (as per Section 1.3), we identify several essential tools. Our proposed technological pillars strongly link to the following recommendations from [4]:

1. *Open Educational Resources*: A large growing collection of freely available and accessible educational resources with appropriate diversity to suit a global learner population.
2. *A unifying taxonomy of knowledge*: A region-, government- and language-agnostic representation of knowledge that can be used to build AIEd tools (we propose Wikipedia as a foundation).
3. *Human-centred AI*: A suite of fair, interactive, collaborative and transparent AI algorithms that give full agency to the stakeholder.
4. *Streamlined and solidified regulation*: A series of well-thought-out regulations that can govern the development of AIEd tools that can positively impact the globe as a whole.

Within the human-centric AI pillar, we emphasize the need for *open science* [62], which can promote engagement with state-of-the-art know-how *open source* to promote community engagement, and *foundational AI models for education* [41,42], which will help stakeholders to build intelligent education support tools with efficient resource allocation. We believe that both open education and open source are essential foundations for enabling civic engagement with technologies [63]. These could empower and emancipate communities by not only allowing them to easily adopt such tools and resources but also enabling them to change them to their own needs and participate in their design and business models, improving independent experimentation and locally situated economies. We argue that by designing these tools together as a community, we can set the goals and fundamentals of these technologies right. Making science open and software artefacts open-source gives rise to resilient civic societies that are largely independent of the global infrastructures and allows them to tap into their local resources and knowledge [63]. Moreover, AI systems are fundamentally socio-technical, including the social context in which they are developed, used and acted upon. The processes by which systems are developed entail a long list of decisions by designers, developers and stakeholders, with many of them being of societal, legal or ethical nature [49]. Thus, AIEd solutions should be accompanied by critical documentation [64] that states the design rationale, as well as any limitations of the educational datasets/tools/resources and the context in which they were developed. This idea also supports the open-science concept, whereby the process of developing scientific knowledge is documented for transparency [62].

3.1. Open Educational Resources (OERs)

Open Educational Resources (OERs), a term coined at the UNESCO Forum on the Impact of Open Courseware for Higher Education in Developing Countries (2002), are now being adopted by many governments and schools as a low-cost, scalable and inclusive alternative to the high cost and lack of diversity of textbooks. Identifying critical barriers surrounding access, quality and costs of information and knowledge available over the Internet, the OER initiative was founded to improve global access to knowledge [65] and calls for access and equity. More specifically, OERs are openly licensed educational materials (for teaching and learning) distributed publicly on the Internet with an open license that permits no-cost access, also enabling others to retain, reuse, revise, remix and redistribute content [27]. The OER Paris Declaration endorsed that OERs may contribute to social inclusion, improve gender equity and encourage education for those with special needs; promote lifelong learning; and make teaching and learning better in quality and more cost-efficient [66]. Stakeholders believe that OER use enables developing countries to improve the quality of education (74.45%), access to learning materials (77.75%) and lower educational materials costs (80.88%) according to global surveys on OERs [67,68].

This innovation succeeds in scaling rapidly by providing a toolkit that minimises the effort of creating teaching materials from scratch (e.g., through innovative licensing schemes and aggressive growth models such as the content explosion model [69] and open educational practice [70]). The success of this innovation also stems from the community's tendency to constantly facilitate design hackathons [71,72] that connect designers, educational practitioners, developers and other stakeholders to sit at the same table to develop solutions. The true potential of OERs is only starting to show tangibility, with OER collections accumulating more than 100,000 materials, with these having been curated, translated to multiple languages using AI, as well as transcribed and annotated using AI technologies [20,30]. With the use of support tools such as interactive translation systems [73], the cross-lingual translation of educational materials can be expedited, making many rich educational resources available to diverse communities in their native tongues. The feasibility of enriching these materials and presenting them to users in an intelligent user interface has been demonstrated recently [38]. Accessible formats or templates for creating accessible content for all learners can be built in from the start [39]. Furthermore, these materials are now accessible and discoverable by the world population through the use of AI to mitigate information overload and provide personalised knowledge to individuals [29]. The meta-analysis in [74] reported no differences in learning efficacy between open and commercial textbooks and showed that student withdrawal with open textbooks was lower than with commercial textbooks. However, ensuring quality in OERs often remains a significant challenge [69].

Rather than predefined curricula, inclusive AIEd needs to offer dynamic paths for users to choose from in an informed fashion. Enabling the user to make informed decisions and allowing for a mutually productive dialogue between the human and the machine should be one of the primary goals of AIEd. This is in contrast to the prevalent use of recommender systems, where suggestions are only presented in one direction from the system to the user. To offer such flexibility to a diverse world population, a mammoth of learning material should be at the disposal of the personalisation system. OERs are among the few collections of learning materials that can suffice this requirement with minimal legal and commercial restrictions.

A collaborative culture with a networked community of those engaged in teaching, training, lifelong learning and community development is essential for OER success [75]. While the initial investment for OERs may be higher, the overall cost will drop with increasing use of OERs [76]. OERs are steadily becoming available, providing many pedagogical opportunities to improve teaching and learning environments. This happens through increased access to knowledge and facilitating opportunities for learners to co-create learning materials. Now, in post-pandemic times, OERs may help us to move globally towards more resource-based, networked, culture- and gender-sensitive, collaborative open learning, and OERs and open educational practices are critical to developing such a culture of openness [76]. In our view, the OER initiative represents the most promising cross-domain, culturally diverse collection of materials for democratising inclusive education.

3.2. Wikipedia, a Dynamic, Scalable Knowledge Base

The need for unifying knowledge base and taxonomy has been one of the greatest challenges faced by the AIEd community since its inception. This is essential for the large-scale deployment of AIEd systems. Since AIEd solutions cannot rely on handcrafted annotations, the common approach used for ITSs is to work with a limited number of learning materials and learners at a given time (a course, an examination or a MOOC) [31]. This is a major limitation for ITSs to scale to deliver their long-promised benefits. A lifelong educational system will need to understand the universal structure and direction of knowledge (e.g., identify knowledge prerequisites), the topics covered and the difficulty of educational materials, while filtering them by metrics of quality assurance, with the goal of matching the most appropriate learning materials to learners. All of this needs to be achieved across multiple modalities of knowledge, languages and cultures.

With the inception of foundational AI models, Large Language Models (LLMs) have been shown to be neural knowledge bases [77] that can store relational knowledge. However, relying on LLMs for world knowledge can pose multiple challenges. Firstly, they are statistical language generators at their core, prone to creating factually inaccurate outputs (so-called LLM hallucination/confabulations) [78]. Furthermore, the worldview LLMs hold is trapped in a black-box embedding space that is not intuitive to humans. Humanly intuitive tools in education have been shown to enhance learner trust and trigger self-regulation [79–81], which are essential for informal lifelong learning. These points further support the utility of a symbolic knowledge base instead of considering LLMs our only option for relational knowledge storage.

On the other hand, Wikipedia remains the world's largest and most up-to-date encyclopaedia. It achieves this by (i) using technologies that support humans to contribute information and (ii) including crowdsourcing at the heart of every aspect of Wikipedia. Wikipedia also leverages AI to help scale this human information management operation, for example, by augmenting intelligence in article quality assessment [82], defending contributors from abuse [83] and various other tasks [84]. While many scholars remain unaware of the growing consensus around the quality of Wikipedia's content [85], many studies are showing that the knowledge is trustworthy [86] and that the number of errors it contains is on par with the professional sources even in specialised topics such as biology or medicine [87].

We envision many opportunities to utilise social and collaborative encyclopaedias (such as Wikipedia) to create educational tools supporting equitable lifelong learning. First, as a universal knowledge base, Wikipedia can become the common taxonomy enabling interoperability among different educational standards and materials that belong to different nations and educational systems. The feasibility of such an approach has already been proven in other domains. For instance, knowledge extracted from the Wikipedia graph has played a key role in cross-mapping national Industry 4.0 taxonomies created by different European nations [88,89]. Wikipedia has shown the potential to become the common ground that connects diverse proposed taxonomies. Similarly in education, many governments and organisations have invested resources and expertise in developing curricula, taxonomies, teaching guidelines and learning resources that uplift the quality of education in local contexts. However, this localisation has posed serious challenges, as cross-compatibility of knowledge is missing [71], leading to challenges in the reuse of learning materials. Many use cases leveraging Wikipedia for education have been emerging recently [40].

Using novel entity-linking approaches [37,90], there is an opportunity to ground curricula that originate from different systems into a single taxonomy, allowing the global population to discover relevant educational materials that are enriched beyond their local environments. The utility of such a global taxonomy has already been shown in social media [91] and educational recommenders [29]. Secondly, having a humanly intuitive taxonomy in its foundation (as Wikipedia does) also allows for the embedding of expert supervision and scrutiny into the process [92,93]. Finally, such grounding opens up avenues to cross-disciplinary lifelong learning experiences (across time, language and geography) as the global taxonomy is domain-agnostic and convertible to local taxonomies. While the Wikipedia link graph alone is a rich source of universal knowledge, there is a portfolio of auxiliary data structures that surround Wikipedia and provide much richer information. Ontologies such as Wikidata [94] and DBPedia [95], which are built on top of Wikipedia, unlock higher-level information that can be further useful. These ontologies provide additional information, such as concept types (e.g., persons, locations, events, etc.) and relationship types (e.g., "sub-topic of"), which allow both computers and human stakeholders to exploit the Wikipedia knowledge base to improve AI-powered education. Wikipedia, as an open platform, also comes with its weaknesses, such as exposure to social biases and challenges in fact-checking. Being run on social contributions, Wikipedia is exposed to coordinated manipulation. Contributors carrying competing interests may get into "edit wars" and impact the correctness of information in Wikipedia [96]. However, by acknowledging and identifying such weaknesses, we can work towards mitigating these and engage with stakeholders to uplift the quality of this living taxonomy.

3.3. Human-Centred Tools

When deploying AIEd, we need to consider the prevalent learnings from AI for the social good and developing nations' research [97]. We need to make sure that we are mindful of asking the core questions:

- Are we accounting for the technological, societal and cultural differences across nations?
- Are we ensuring that the interests of low- and middle-income countries are represented in key debates and decisions?
- Are we creating the necessary bridges between these nations (end users) and countries where AI is currently being developed (producers)?

Currently, the majority of AI solutions we create revolve around *ideal* scenarios defined by datasets that are created in controlled environments in the developed world. First of all, we must ensure that our test beds do not differ significantly from real-life imperfect settings in which these solutions will operate and that we engage all stakeholders in the design process.

To support such an idea, AI-based educational tools must embrace design patterns within the umbrella of human-centred Machine Learning [98]. This may sound like a vacuous statement, as human-centred AI is a vast area of research. Putting the learner at the epicentre of the design of the tools gives them agency to interact with these tools and scrutinise them (e.g., by querying their biases and beliefs, changing the optimisation goals and, importantly, designing their personalised learning tools). In addition, a human-centred approach to AIEd provides opportunities for better value alignment of AI tools and their intended end user [99]. In the framework of AI in education, we would require both humans and machines simultaneously in the loop [12]. This means machines assist learners while they learn and learners guide and govern these machines. Usually, a human-in-the-loop approach requires humans to give feedback to the algorithms to learn. This could be a mix of explicit and implicit feedback [29]. Allowing for hybrid human–machine interaction and collaboration is of crucial importance in such an educative system to give the stakeholder full control and access to manipulate their own personalised learning tools and to put the tools at their complete service (e.g., self-governance of one's models [100]). This setup also fosters ownership and builds trust [97]. Such a shift will move AIEd from prescriptive algorithms to collaboration with the human. Part of these requirements apply not only to AI but more generally to the design of user interfaces or human–computer interactions.

3.3.1. Explainable and Transparent AI

Transparency and privacy should also be key to such systems, allowing stakeholders to understand the potential and limitations of these algorithms and to decide what data the algorithms should store and use for reasoning, as well as changing the model when needed (for example, when the user believes the model is biased) [100]. This could mean that humanly interpretable latent variable models should be preferred over their black-box counterparts [29]. However, transparency is a subject-specific concept with multiple layers, in the sense that what is transparent to an AI researcher might not be transparent to a teacher or a student [101]. Therefore, the transparency of systems should be considered from their intended end users' point of view and the machine needs to take a full supporting role, with users ultimately having control over when and how to use the tools. This "how" could mean that users may decide to boost certain variables in the system. For example, a user may decide to enhance serendipity in a recommendation system to obtain access to educational resources they may not have found otherwise or to enhance novelty to get exposed to more novel material. Contestable and scrutinisable models are also of key importance [102]. We argue that trust from the user is more likely to be achieved by demonstrating transparency in AIEd tools [79,92]. Emerging evidence from teachers' trust in AIEd tools indicates the value of increasing transparency, teachers' knowledge of the tool and their agency in the decision-making of the tool as significant contributors to improving teachers' trust and further adoption of these technologies [103].

3.3.2. Open Models, Open Science and Open Source

The advancements made in foundational AI models (LLMs [104], vision [105] and various pre-trained multi-modal models) have shown promise in increasing the potential of human capital to carry out support roles in education. Recent experiments show the viability of using LLMs as the base for building intelligent educational systems capable of question generation, question answering, learning content generation, and summarisation [41,45,106,107]. It is noticeable that a wealth of this research relies on commercial offerings. However, opening up trained model parameters of large language models such as Google T5 [108] and Facebook Llama [104] has turned a new page, democratising the utility of such AI capabilities. There is already work showing promising results in further pre-training these models for educational settings and demonstrating the usability of small language models that are more manageable from an infrastructural viewpoint with acceptable predictive performance [41].

Opening foundational models is a booster for democratising these tools. Further documenting the developmental process behind such models openly enhances adaptability [97]. The clear and open documentation of the experimental setups of such models also provides tremendous transparency when hypothesising generalisability. The open-science framework provides a rich framework to carry out this documentation process with tools. The AIEd community is also encouraged to use such a framework, as many scientific discoveries in the field rely on both technological prowess and user studies [62]. Such transparency will also improve efforts towards understanding the ethical and fairness aspects of new technologies before mass adoption [98].

To provide the effective utility of AI tools in developing nations, open-sourcing the source code in addition to the scientific method is a trivial enabler. The OER community and Wikipedia contribution network have also learned a lot from the open-source movement and its success in democratising software [109]. However, open-sourcing sophisticated AI solutions would not magically enable developing nations to leapfrog, as there is a necessary knowledge transfer that should happen to build both operational and human capabilities to work with cutting-edge tools. In failing to collaborate with the end consumers, we fall back to techno-solutionism.

Techno-solutionism describes the belief that technological solutions on their own can solve complex real-world challenges, whereas in reality, these technologies are made by humans, and as such, they can be subject to design flaws, prejudices, bias, lack of cultural context and a wide range of other socio-technical factors [110,111]. Techno-solutionism also entails faith in technology [112] but also, importantly, a tendency to fundamentally change how we perceive and analyse social phenomena, often neglecting their complexity or interconnectedness [111]. This simplification of complex (often structural) challenges is the main aspect of techno-solutionism that we wish to emphasize in this work.

From an appropriate technological perspective, collaborations between experts and beneficiaries would pave the way for knowledge and skill transfer, although obviously, this takes time [97]. Another interesting trend in recent years is simplifying the interface between complex systems and users by building a no-code/low-code layer in between. Low-code systems allow for rapid digital transformation, enabling entities to (1) digitise processes to increase visibility and management of artefacts (documents), (2) enable automation or semi-automation of certain mundane, repetitive tasks and (3) use the digital footprint to integrate with external systems and also change current processes for the better. Introducing low-code interfaces has shown strong evidence in enabling non-technical users to tap into powerful computational systems without being overwhelmed by the complexity of the systems [113]. We can also see this trend emerging in the AI domain with model-as-a-service platforms that obfuscate the complexities of maintaining infrastructure for ML [114].

3.3.3. Impact of Human-Centred AI

We assert that a pivotal role of AIEd (and an ambitious challenge) will be to move towards innovative emerging pedagogies, such as formative analytics (where learners are provided with information for self-regulated learning) [100], teach-back (providing learners with an opportunity to teach their learnings) and learning with robots (where repetitive tasks such as assessment and hint giving are automated to free up teachers for cognitively demanding tasks) [115]. With the right adaptation of AI-based education, these novel pedagogies could unleash potential on a global scale. Other futuristic pedagogies, such as place-based learning [116] and citizen inquiry [117], which revolve around engaging learners in participating in an active problem-solving environment, could also foster great potential benefits. In the context of sustainable development and education, empowering non-technical stakeholders such as social scientists, policymakers and even educators is possible by using low-code systems that allow for the harnessing of AI and advanced data analysis capabilities with limited/no coding experience [118].

3.4. Unified Vision for Regulated AIEd

AI could impact education greatly. However, limited robust research has been undertaken at this point; very few guidelines have been agreed upon; and policies are still under early development when it comes to regulating the use of AI in education (mainly limited to the higher education sector [119,120]). In this sense, a well-designed framework for engaging with the ethics of AIEd is vital [98]. It is time that we decide collectively what technology-enhanced education should mean, with the end goal of increasing access to high-quality education for all. Such a strategic effort will allow for the streamlining of the different stakeholders together, where the political agendas, scientific agendas and financial support can be aligned with a clear vision of delivering positive outcomes.

4. Concluding Remarks

At the moment, the field is devoting much attention to personalised intelligent tutors. However, such ambitious use cases, essentially proposing to replace teachers, are far from delivering any impactful and real-world results. We argue that massively investing resources in such technology poses the risk of misallocating necessary resources to enhance the current lack of access to high-quality education around the globe. Therefore, the community should also focus on other important aspects of AI in Education, such as tools that support the role of teachers and make education more inclusive while, at the same time, building a strong basis (in socio-technical terms) that could, in the future, support personalised intelligent tutors research.

Perhaps, if correctly designed and deployed, AI tools could deliver, in the long run, on their potential for (i) providing at-scale empowering access to education beyond any political, cultural, language, geographical and learning-ability barriers; (ii) helping us create fulfilling, equitable and inclusive lifelong learning schools of the future; and (iii) leveraging the so-called renaissance of new ways of teaching and learning. The pillars proposed in Section 3 support this delivery. OERs and Wikipedia are core to the democratisation of knowledge in a scalable and equitable manner, supporting (i) and (ii). Human-centric tools that are open to everyone (open models, open science, open source, etc.) support equity and innovation, supporting (ii) and (iii). Healthy and unified regulation provides a safe and solid roadmap for future innovation that safeguards equity, fairness and ethical responsibility, supporting (i), (ii) and (iii). Figure 1 summarises the structure of this work.

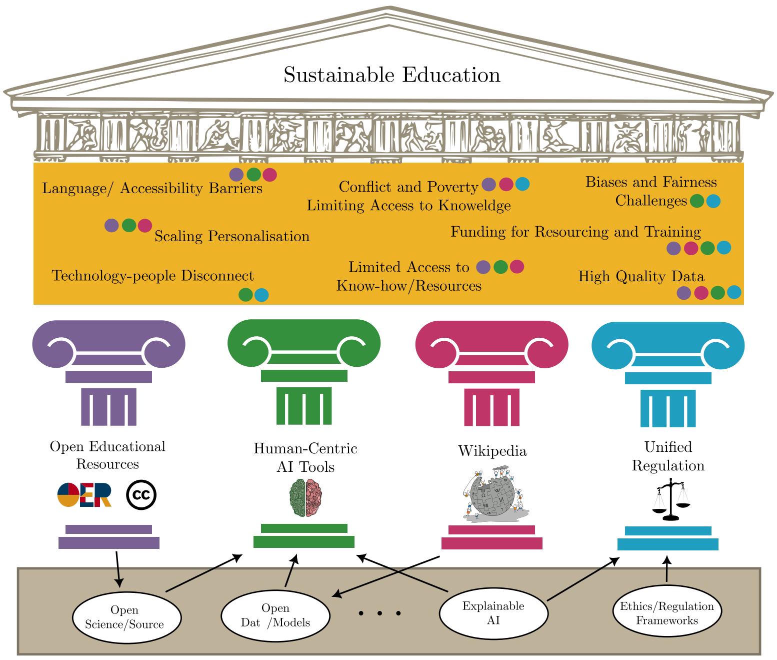

Figure 1. Leveraging Artificial Intelligence to create a scalable, equitable and sustainable AIEd ecosystem. The four pillars and how they can address several key challenges towards sustainable education (using colour-coded circles) are presented.

There are enormous technical, social, political and pedagogical challenges ahead for the field of AIEd. These are issues related to data and algorithms; to pedagogical choices; to inclusion and the 'digital divide'; to learner's/teacher's right to privacy, liberty and unhindered development; and to equity in terms of gender, disability, social and economic status, ethnic and cultural background, and geographic location [22]. However, like with any other technology, the greatest challenge is how to design them to be a driver of equity and inclusion and not a source of greater inequality of opportunity, as pointed out in Section 2.

We aimed to discuss a subset of these, with the hope of starting this dialogue and collectively designing a global education revolution that will help us make progress to address educational inequity. Motivated by the need to create a sustainable, large-scale and inclusive AIEd ecosystem (Section 1.3), we propose a socio-technical solution to meet part of these challenges and encourage colleagues to avoid simple techno-solutionist [112] approaches to AIEd research and innovation (i.e., relying simply on technological fixes that do not acknowledge and consider the complexity of education challenges):

- Working together on developing and leveraging the power of language and culturally diverse Open Educational Resources (OERs), which can be reused and consumed around the globe.
- Building standardised taxonomies and ontologies of knowledge (like Wikipedia), is one of the greatest technical challenges for AIEd at present.
- Investing in human-centric scientific advancement that entails open science, models and source code to enable civic engagement with the design of these technologies and thus support their sustainable use in local communities.
- Engagement in critical thinking and policymaking, where we question the social norms and politics embedded in AIEd systems and direct technological change towards meeting societal needs and reducing inequalities.

Before committing to a future where AI pervades learning, educationalists and technologists need to guide society and governments to understand the potential pedagogical, social and ethical implications of this technology [49]. Engaging in speculation when designing technology is of crucial importance. We provide now a non-exhaustive list of question examples we think the field of AIEd should be asking, building on our previous discussion.

Regarding technical terms, we could ask the following: What is the nature of knowledge, and how can it be represented and captured with AI? How could an AI system automatically gather, understand and filter educational resources suitable for each learner's needs? How can AI help bridge the education gap for learners with disabilities? How can AI-based tools prioritise transparency, keeping the human in the loop to support users to self-reflect on their learning path and give them agency? What learning metrics, if any, should guide these learning tools and algorithms? How can personalisation algorithms support our diversity as individuals and communities? Regarding the social aspect, we could ask the following: How could we scrutinise any biases as well as social prejudices embedded in these techniques? How can we collectively identify and document the limitations in educational datasets/tools/resources? How can we support our communities to engage with the design of educational tools that concern us all? How can we all learn to identify faulty educational tool designs that plague the most vulnerable and collectively correct these? How could we successfully and safely iteratively prototype and evaluate these tools in the wild? Regarding pedagogy, some key questions examples could be the following: How can we promote design thinking in educative settings, where we allow "what's wrong?" to drive our pursuit of "what if"? Could, ultimately, these AIEd systems engage communities to transform individuals, communities and the environment? How can such a system encourage critical and emerging pedagogies?

Ultimately, the question we, as a research collective in AIEd, need to ask (and work towards) is the following: What would it take for AI to help us democratise quality education for all? We claim that AI on its own cannot offer a solution. Instead, we should aim to address the political and social issues behind the unequal access to high-quality education and take these issues into account while developing AIEd tools and solutions using socio-technical approaches. The pillars of considerations proposed in this paper are likely to contribute towards such an approach to AIEd.

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Abbreviations

The following abbreviations are used in this manuscript:

AI	Artificial Intelligence
AIEd	Artificial Intelligence in Education
LLM	Large Language Model
IDIA	International Development Innovation Alliance
IRCAI	International Research Centre on Artificial Intelligence
ITSs	Intelligent Tutoring Systems
ML	Machine Learning
MOOCs	Massively Open Online Courses
OECD	Organisation for Economic Co-operation and Development
OERs	Open Educational Resources
UNESCO	United Nations Educational, Scientific and Cultural Organisation
WIDE	World Inequality Database on Education

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