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AI in a globalised world: The educational context of cultural and linguistic biases

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Generative AI tools, including large language models (LLMs), have witnessed increased popularity and have predominantly been trained using human-generated inputs. Nevertheless, as these AI models continue to expand across the Internet, there is a possibility that computer-generated content may be employed to train other AI models – or themselves – in a recursive loop. In this context, the issue of globalisation and its effect on AI-generated content appears to be a matter of increasing urgency. This paper explores how artificial intelligence is taught, used, and perceived in different cultural and educational contexts. It also examines the implications of cultural biases embedded in large language models, the challenges of diversifying training data, and the ethical responsibility of AI deployment in global education systems.

generative AI, large language models (LLMs), cultural bias, AI in education

1. Introduction

The development of Artificial Intelligence (AI) is leading to the creation of a fascinating and dynamic environment in various fields. In the contemporary era of accelerated progress in digital technologies and machine learning, novel prospects are emerging for integrating artificial intelligence. Education is becoming an area of significant focus for applying artificial intelligence. Nonetheless, numerous issues must be addressed in the context of educational applications of artificial intelligence, whether by teaching professionals or learners.

Integrating artificial intelligence into education necessitates a comprehensive understanding of cultural contexts, impacting the adoption rates and the perception and utilisation of AI-driven tools (Ożegalska-Łukasik, Łukasik, 2023). Cultural nuances play a pivotal role in shaping individual attitudes toward technology, influencing the acceptance and integration of AI in classrooms globally. Therefore, educational strategies must be adapted to resonate with diverse cultural values and norms to ensure effective AI implementation (Gentile et al., 2023). Educational policies should integrate a careful understanding of cultural values and identify contexts where interventions are necessary, as AI integration raises questions about teachers' roles and the ethical implications of data collection. In order to guarantee that Artificial Intelligence is employed in pedagogically rich and ethically challenging ways, it is crucial that specific

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ethical, pedagogical, digital and technical competencies are cultivated among educators (Kalniņa et al., 2024). It is vital to foster critical reflection and cultivate human intelligence alongside artificial intelligence (Ma et al., 2024).

The development and training of language models, a cornerstone of AI applications in education, are intrinsically linked to the cultural data they are trained on, where the data sets used to train these models often reflect the cultural biases and perspectives of their creators, potentially leading to skewed or irrelevant outputs in different cultural settings (Roshanaei et al., 2023). This can inadvertently perpetuate stereotypes or exclude certain cultural narratives, highlighting the need for diverse and representative datasets in AI training (Adams et al., 2023). It is important to note that there is a tendency to either understate, or indeed to overlook entirely, the complexities and potential issues that arise from the integration of AI within educational settings (Al-Zahrani, 2024). The ambition of creating personalised learning experiences through AI, although carrying considerable promise, could inadvertently marginalise educators' crucial role in students' holistic development (Bulathwela et al., 2024). As Paliszkiewicz and Gołuchowski (2024) describe, "*the outcomes delivered by AI depend on its design and the data used. Both the design and data can be biased, either intentionally or unintentionally*". It is therefore imperative to emphasise the increasing significance of critical thinking in the context of information literacy, and the crucial role it must play in the educational process.

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2. The learning process of the AI

The issue of the origin of the input sources applied by the AI to produce the results is crucial. As Kumar (2019) states, artificial intelligence learns through a multifaceted process involving algorithms, data, and computational power, enabling systems to mimic cognitive functions. This learning is primarily achieved through machine learning, a subset of AI that allows systems to improve from experience without explicit programming.

It is widely acknowledged that "*machine learning algorithms can be broadly classified into four categories: supervised learning, unsupervised learning, semi-supervised learning, and reinforcement learning*" (Pugliese et al., 2021, p. 20) (Fig. 1.).

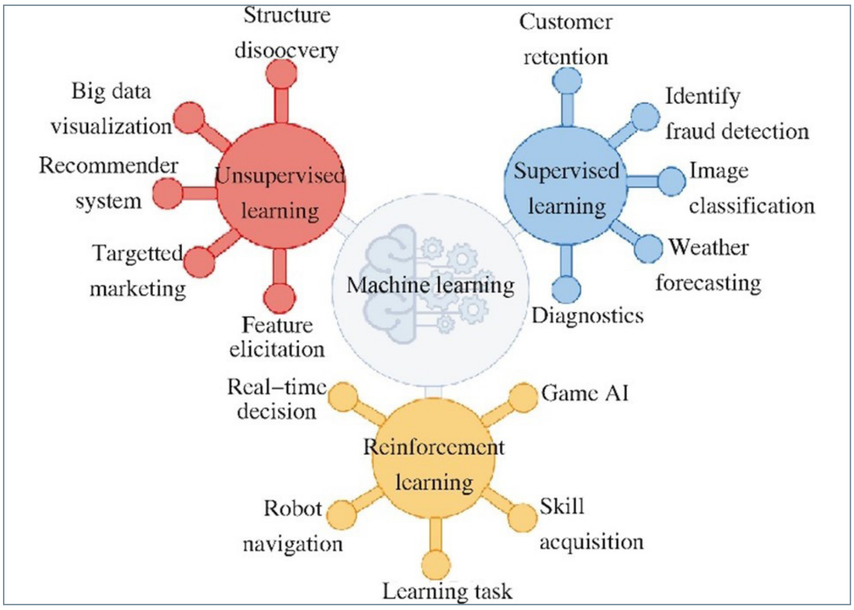

Fig. 1: Machine learning algorithms classification (Pugliese et al., 2021)

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Supervised learning is a process whereby artificial intelligence (AI) models are trained on labelled datasets. These datasets contain both the input and the desired output, thus enabling the model to learn the mapping function (AlTwijr, Alghizzi, 2024). The algorithm is designed to identify patterns and relationships within the data set. It then uses the established model to predict outcomes for new, previously unseen data (Liao, 2023). In contrast, the process of *unsupervised learning* involves the training of models on unlabelled data. In this scenario, the algorithm is required to discern latent patterns or structures without the provision of explicit guidance (Owoc et al., 2021). Standard unsupervised learning techniques encompass clustering, dimensionality reduction and association rule learning (Yim, Wegerif, 2024). *Reinforcement learning* trains agents to maximise reward signals in an environment through trial and error, receiving feedback in the form of rewards or penalties for their actions. Agents learn through trial and error, with feedback serving as a reward (Gillani et al., 2023). According to Choudhary et al. (2022), "*deep learning (DL) is one of the fastest-growing topics in materials data science, with rapidly emerging applications spanning atomistic, image-based, spectral, and textual data modalities. DL allows analysis of unstructured data and automated identification of features*". Inspiration for these networks is taken from the structure and function of the human brain, and these networks have the capacity to learn intricate features and representations automatically from primary data (Gillani et al., 2023; Zawacki-Richter et al., 2019).

The core principle of AI lies in the idea that intelligence is a computational process that can be replicated by machines, leading to the creation of diverse approaches like symbolic AI, which uses logic and knowledge representation for reasoning, and connectionist AI, which uses neural networks to learn from data (Rani, 2020). As Michaeli et al. (2023) notes, the knowledge that has been acquired is organized within a model and can be utilized in different contexts or with new data. The efficiency of AI learning relies heavily on the availability and quality of data, with more extensive and more diverse datasets generally leading to better performance (Rani, 2020; Wang et al., 2023). Furthermore, the choice of learning algorithm and the architecture of the AI model significantly impact the learning process and the resulting performance (Azuaje, 2019; Harkut, Kasat, 2019; Khanam et al., 2024; Lv et al., 2024).

3. Cultural and linguistic biases in AI systems

Artificial Intelligence (AI), especially language models like ChatGPT, is reshaping how we access knowledge, learn, and communicate. Over the past two decades, globalisation has increasingly homogenised the world economically, culturally, and linguistically. As a result, AI systems often produce standardised, "*plastic*" responses that lack depth and cultural specificity, alienating users from diverse national and linguistic backgrounds.

A core issue is that most AI models are trained primarily on English-language datasets, often heavily influenced by American culture. Consequently, when these models interact with users from different linguistic and cultural contexts, their responses can seem foreign, superficial, or irrelevant. If students increasingly rely on AI for learning, they risk building their knowledge on answers disconnected from their cultural heritage and traditions. This could accelerate the erosion of national identities and contribute to the rise of a shallow, globalised culture.

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Concrete examples highlight this concern. Imagine a student in Hungary asking an AI model about traditional holiday customs. Suppose the AI has only been trained on English-language, American-centric datasets. In that case, it might discuss Thanksgiving traditions or suggest Halloween activities – both culturally irrelevant in a Hungarian context. Similarly, when asked about national cuisine, the model might recommend "*burgers and fries*" instead of traditional dishes like "*gulyás or töltött káposzta*" (*goulash or stuffed cabbage*) In educational settings, such misalignments could gradually replace native cultural references with imported, generic content.

A fitting analogy can be drawn from gastronomy: the global spread of McDonald's represents a homogenisation of food culture. In countless countries, McDonald's has replaced local flavours with standardised menus designed for mass appeal but lacking national cuisines' richness, tradition, and depth. Similarly, if AI is not taught using national languages and cultural contexts, it risks becoming a fast-food version of knowledge – convenient, consistent, but ultimately detached from meaningful local heritage.

To prevent this, training AI systems in national languages with strong incorporation of local cultural content is vital. National libraries, cultural institutions, and educational organisations must collaborate with AI developers to create authentic language and culture-specific datasets. National libraries, as custodians of a country's linguistic and cultural heritage, can provide invaluable resources, ranging from literary works and historical documents to folklore and oral traditions, allowing AI to understand better and respect local contexts.

This effort is not merely technical but fundamentally cultural. Without it, uniformity in this context – carried by technology – might lead to impoverished global culture. Stronger cooperation between national institutions and AI developers would advance technological innovation and ensure the survival and flourishing of diverse cultural identities in the digital age.

The consequence of the scenarios mentioned above could be the phenomenon of "*model collapse*", which is currently occupying many researchers (Shumailov et al., 2024; Bohacek Farid, 2025; Gerstgrasser et al., 2024; Peterson, 2024; Seddik et al., 2024). Shumailov et al. (2024) define model collapse as "*a degenerative process affecting generations of learned generative models, in which the data they generate end up polluting the training set of the next generation. Being trained on polluted data, they then mis-perceive reality*". Moreover, Shumailov et al. (2024) contend that in this scenario, the models do not simply overlook previously acquired data; rather, they initiate a process of misinterpretation, perceiving what they assume to be accurate through the consolidation of their existing convictions.

The potential applications of AI in educational settings include students using artificial intelligence to complete their homework assignments. Evidently, in this instance, the formulation of appropriate prompts is crucial. However, it is essential to emphasise that the interpretation and utilisation of AI output necessitates a critical approach. As demonstrated in Fig. 2, the issue of model collapse can be illustrated by presenting a potential sequence of steps for resolving and managing homework assignments with the assistance of artificial intelligence.

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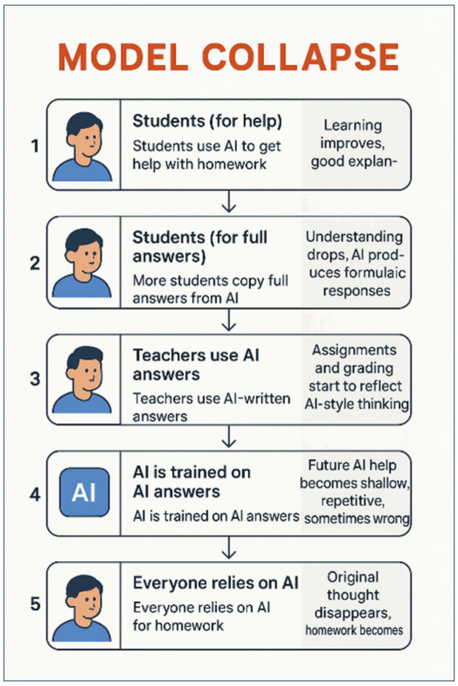

Fig. 2: Illustration of Model Collapse in Educational Context (Open AI, 2025)

Considering the increasing prevalence of AI in content creation and publication, Carl Franzen, digital media strategist, poses the following obvious question: "*What happens as AI-generated content proliferates around the internet, and AI models begin to train on it, instead of on primarily human-generated content?*" (Franzen, 2023, para. 3). The origin of data for machine learning has become a particularly relevant topic in recent times, as machines can now access a vast array of data sets originating from artificial intelligence itself, which were not available to them in the past. This development represents a significant shift from the traditional human-created data sources, such as books, studies and photographs, which were previously the primary sources for machine learning. It is important to note that this could lead to a feedback loop characterised by the neglect of diversity and cultural pluralism, or even the rise of prejudice and the dissemination of information from irrelevant, unfounded sources. In this instance, the "*globalised and uniformed*" responses question is highly significant, as the feedback loop process can contribute to this phenomenon.

According to the European Union Agency for Fundamental Rights (FRA, 2022), a feedback loop occurs when predictions made by a system influence the data used to update the same system, meaning algorithms can influence each other by shaping the reality they later analyse. As demonstrated in Fig. 3, a simplified outline of the feedback loop, it is evident that the influence is two-way, with both the real world and AI impacting each other.

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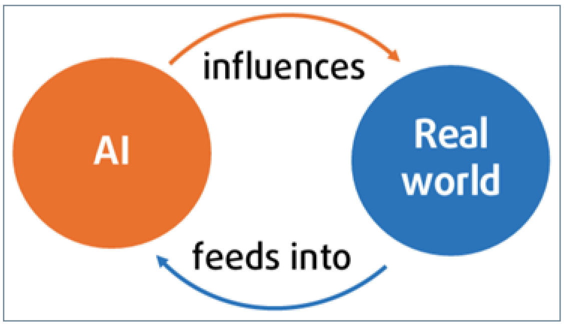

Fig. 3: Simplistic illustration of a feedback loop (FRA, 2022)

3.1 The educational context of the problem

The pervasive influence of globalisation on information access necessitates a critical examination of cultural and linguistic biases embedded within artificial intelligence systems, particularly those employed in educational contexts (Rusmiyanto et al., 2023). The ability of students to access information from around the globe with little difficulty is having a significant impact on learning approaches. However, this increased access is not without its challenges, primarily when it is mediated by artificial intelligence (Yusuf et al., 2024). AI algorithms, designed to curate and deliver information, are often trained on datasets that reflect their creators' cultural and linguistic norms, typically originating from Western, educated, industrialised, rich, and democratic societies (Samuel et al., 2023). The report by the AI Now Institute (Kak, Myers West, 2023) highlighted the concentration of AI development and power in Western nations, particularly the United States and Europe, where major tech companies dominate the field. Similarly, the 2023 AI Index Report by Stanford University highlights the significant contributions of these regions to global AI research and development, reflecting a clear Western dominance in datasets and innovation.[1]

This inherent bias has the potential to inadvertently skew the information presented to students, potentially marginalising perspectives from non-Western cultures and reinforcing existing imbalances (Darwin et al., 2023).

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In integrating artificial intelligence technology into education, it is essential to consider the cultural context, including the local and regional dimensions and linguistic preferences. AI literacy could play a significant role in the mentioned process. AI literacy emphasizes the need of applying a critical mindset to the information gathered while providing educators and students with the skills they need to use AI tools efficiently. Černý (2024) identifies five major approaches to AI literacy in academic literature:

- "*AI literacy as a competence for everyday life*;"
- "*AI literacy as a prerequisite for future success in the labour market*;"
- "*AI literacy as part of the competence structure*;"
- "*AI literacy as a composite structure*;"
- "*AI literacy is a form of technical knowledge and skills*."

As Turós, Nagy, and Szűts (2025) argue, using artificial intelligence consciously is one of the most important skills required in the twenty-first century. There are three primary components to the debate over the conscious application of artificial intelligence:

- "*Understanding the basic concepts and operating principles of artificial intelligence: students should be able to understand machine learning, natural language processing, and various applications of artificial intelligence.*"
- "*Knowledge of ethical and legal aspects of artificial intelligence: students should be able to assess the potential moral and legal risks of artificial intelligence and consider these when designing and using systems.*"
- "*Critical evaluation of artificial intelligence-based systems, so that students can recognise potential errors and limitations of the systems.*" (Turós, Nagy, Szűts, 2025, p. 9).

The AI Index 2025 Annual Report (Maslej et al., 2025) differentiates between AI in education, AI literacy, and AI education. "*AI in education is the usage of AI tools in the teaching and learning process, while AI literacy refers to the foundational*

[1] https://www.unite.ai/western-bias-in-ai-why-global-perspectives-are-missing/ (Accessed: 2025.05.19.)

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understanding of AI—how it works, how to use it, and the risk of using it. AI education encompasses AI literacy plus students' proficiency in the technical skills required to build AI (data analyses undergirding AI technologies, identifying and mitigating data biases, etc.)" (Maslej et al., 2025, p. 368). Furthermore, the report indicates that a 2024 survey of 364 computer science teachers revealed that 88% of respondents identified a need for augmented resources to facilitate professional development in AI, with a particular emphasis on AI literacy (i.e. the functionality of AI, its utilisation, and the ethical dimension of AI).

In the context of the use of AI in education, Kočková et al. (2024) states that "*there is a foundational understanding of AI among educators, there is a pressing need for targeted professional development to deepen their knowledge and confidence in advanced AI concepts. Addressing technical barriers and providing adequate training and support are essential steps towards successful AI integration.*"

The quality of the output of any generative model is contingent upon the quality of the data on which it is trained; if the training data contains biases, then there is a strong probability that the model will exhibit similar biases. To illustrate this point, consider a model trained on a set of essays written predominantly by students from a specific demographic group. Such a model might not accurately evaluate essays written by students from other demographic groups. (Baidoo-Anu, 2023)

The impact of globalization on AI-generated content is a significant area of concern, as AI systems are heavily influenced by sources belonging to the "*majority culture*." This may result in the characteristics of other nations and minority groups being marginalised or overlooked. In this context, it is essential to address the issues of model collapse and feedback loops, as the increasing utilisation of AI results in a growing volume of AI-generated content, which, in turn, shapes new content in a cyclical manner.

4. Conclusion

In an increasingly globalised digital environment, where AI systems shape and mediate educational experiences, safeguarding cultural and linguistic diversity has become a strategic imperative. While generative AI offers promising opportunities for personalized and scalable education, its widespread reliance on Anglo-American datasets risks marginalising national traditions, languages, and epistemologies. This risk is not merely theoretical: when students engage with AI tools that fail to reflect their cultural heritage, the very foundation of identity-based learning is eroded, contributing to a homogenised, "*fast-food*" knowledge culture.

To counteract this trend, national libraries must be positioned as strategic allies in AI development. As custodians of a nation's textual memory, national libraries are uniquely equipped to supply curated, context-rich datasets that reflect the nuances of local languages, histories, and worldviews. From digitised folklore and literary canons to academic publications and archival records, these institutions hold the raw materials necessary to train culturally sensitive AI systems. Their collaboration with researchers, AI developers, and educational policymakers is vital for ensuring that artificial intelligence does not overwrite but rather amplifies cultural plurality.

Moreover, national libraries can play an active role in promoting AI literacy by offering open-access tools, educational resources, and critical frameworks that empower educators and learners alike. Through exhibitions, data donation programmes, and partnerships with educational institutions, they can democratise AI access while anchoring it in cultural authenticity. In doing so, they not only preserve national heritage but actively contribute to a more equitable digital future – one where AI supports, rather than supplants, the diverse intelligences of our world.

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