



JRC SCIENCE FOR POLICY REPORT

# On the Futures of Technology in Education: Emerging Trends and Policy Implications

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# Foreword

Digital technologies are not new. They have long permeated our society in the form of devices and software applications that we use for working, studying or personal purposes.

What is new is the dramatic increase in **speed of development and uptake** for these digital technologies. Another novelty is their disruptive and transformative capacities: big data, blockchain, 6G and the new generation internet, artificial intelligence (AI) and the next generation of virtual worlds, are turning upside down the world in which we live, and the way we understand our societies and relations.

We are in the middle of a **new socio-technical revolution** that will dramatically change who we are, how we live and how we relate to one another. In response to this revolution, the EU has the ambition to make this Europe's 'Digital Decade', and to drive a safe and secure digital transformation by 2030, succeeding in the twin digital and green transition.

The education sector needs to adapt to this new, and rapidly changing, information and media environment. Education, both formal and informal, provides fundamental building blocks that define various keys aspects of each person's cognitive development, personality and life opportunities. That is the reason why understanding how digital technologies affect and transform the educational process, and educational systems at large, is key for each society and, in particular, for Europe, in its quest for a human-centred digital transformation.

At the Joint Research Centre of the European Commission, we aim to **identify**

**emerging technologies and trends that play a key role in the transformation of education** across Europe. We also work to understand the ways in which they could shape the future of teaching, learning, assessment, and all other processes and social practices underpinning the delivery of education. Our research aims to anticipate risks, so that policy makers can mitigate them with decisive policy action, but also identify potential opportunities for Europe to develop more inclusive and high-quality educational systems.

This report is part of the Joint Research Centre's effort to **imagine the futures of technology in education** and outline associated **policy implications**. It has the objective to stimulate the discussion, and identify potential scenarios for the use of emerging digital technologies, and particularly AI, in the field of education, going beyond the state-of-the-art and bringing some forward-looking ideas.

We believe it contributes to the crucial debate on the **digital transformation of education** through unfolding some complexities on how these new technologies are likely to affect education. We also believe that this report will serve as a guide to European policy makers to ensure that European educational systems remain effective and human-centred, while adopting emerging digital technologies responsibly.

**Carlos Torrecilla Salinas**

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# Abstract

This report identifies key emerging technologies and discusses their potential impact in education. Drawing on academic research and grey literature, it focuses on a set of ongoing technical developments that could redefine both education and society at large in fundamental ways. It provides insights into the affordances of those technologies and important societal implications, discussing how they may reconfigure education against the background of learning theory. It also considers the socio-material basis of digital technologies, as well as key

factors – such as climate change, demographic transitions, environmental concerns, and the growth of mental health problems among the young – that are shaping the emerging educational landscape. The report aims to go beyond the state-of-the-art and facilitate richer discussions on the potential impact of emerging technologies in education in order to support long-term strategic thinking. Based on that, it offers recommendations to ensure that future policy actions are aligned with the societal and educational needs.



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# Executive summary

Digital technology currently pervades all dimensions of society, playing a central role in our lives. It shapes our everyday existence and has redefined the way we engage in activities related to work, civic participation, health, sports, entertainment and, of course, education. At the same time, technologies are actively shaped by the established practices, dynamics, and values of the social and cultural contexts in which they are conceived, used or embedded in any other ways.

This report aims to map emerging technologies<sup>1</sup> and trends with high potential to influence education<sup>2</sup> and provide a critical perspective on them. It identifies a series of technologies – currently at different stages of development and adoption – which have a high potential to provoke significant societal transformations. The report focuses on how such technologies may contribute to the redefinition of educational practices, processes, and organizations. While offering detailed technical information, the report discusses all these innovations against the background of learning theory, in order to properly unpack their potential influence in teaching, learning and the organization of education at large.

The report argues that the innovation under development that will most likely impact the information and media ecology over the coming years has to do with the connectivity infrastructure underpinning wireless communications. The increase in data transfer speed and the latency reduction

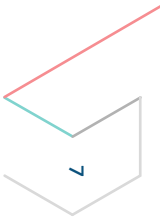
afforded by 5G networks will open up new opportunities, for instance, in relation to immersive virtual environments and extended reality (XR) applications. Eventually, with the rollout of the 6G standard, the internet will operate over a wider spectrum of frequencies and will incorporate a ubiquitous network of highly precise ‘sensing’ devices. The report anticipates that such developments will take the internet to a whole new paradigm of synchronization and blending of the physical and the digital. The so-called Next Internet will constitute a new infrastructure connecting cognition, space, and action in new ways. This will be primarily realized through actionable representations of the physical world, meaning that human action and interaction will become mediated by a real-time digital layer.


In terms of pedagogical implications, the report highlights that the intersections of cognition, space and action are particularly relevant to constructivist theories of learning, which approach practical action as a key source for learning (as illustrated by the thinking of Dewey, Vygotsky and Piaget). Thanks to faster networks, enhanced computing capabilities and lightweight devices, we argue that immersive technologies – such as virtual reality, augmented reality, and holograms – will be able to enable the delivery of authentic experiential learning which would otherwise be unfeasible due, for example, to the safety risks and high costs associated with the real-life experiences that these technologies can help simulate. However, their full potential will only be realized when the physical, social, and digital worlds become interlinked in real time through the connectivity changes described in the report.

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1. New technologies and the continuing development of existing technologies that are expected to be available in the coming years and are could have significant social and economic impact.

2. In this report, the term education is used broadly to cover all types and levels of education.





Learning assessment and competence certification are integral to education, and the report anticipates that emerging technologies could redefine the way in which related processes are organized and how different stakeholders (e.g., educational institutions, employers, graduates) interact with each other. Distributed and decentralised systems – such as blockchain and micro-credentials – are not new anymore, and their disruptive potential was indeed predicted years ago. While high impact remains largely unrealized, micro- and verifiable credentials will probably gain ground in a context where all citizens need to engage in continuous development and upskilling, at least to some extent. This is not without risks as, given the absence of a holistic, inclusive, and quality-driven approach, a digital credentials-driven system also has implications that we need to consider. These kinds of certifications become particularly relevant in a context where the curriculum of formal education needs to be kept up to date at a faster pace. Modularity, allowing obsolete parts to be more easily replaced, is essential here. Nevertheless, when embedding these innovations into educational systems it will be essential to plan for the possibility of the current encryption infrastructures becoming redundant in the not-so-distant future because of advances in quantum computing.

Learning analytics and, more generally, the mining of data in education is already a priority for institutions, policymakers, and educational technology vendors. The so-called datafication of education is only expected to keep gaining ground across all levels and settings, meaning that large-scale data on education will be at the centre of knowledge society transformations. Such data are expected to reinforce and inform the development of new pedagogical approaches, learning technologies, and education policy;

however, it will be necessary to determine which data is required for this and find ways to ensure that all key stakeholders have access to them. The aspiration is to be able to record learning processes, instead of just outcomes, and by doing so to ultimately improve student engagement and attainment. Indeed, datafication of education will not necessarily add value unless the focus remains on the quality of outcomes. However, ethical concerns about personal data processing and their potential misuse need to be carefully addressed, as does the current reliance on infrastructures that are largely in the hands of just a few commercial providers and may pose vendor lock-in or lack of interoperability risks.

AI systems have reached such a level of maturity that there are already products available to the general public that can mimic – and even outperform – humans at certain tasks. In particular, there seems to be broad agreement that generative AI and foundation models will have a lasting impact on education, and there are indeed many examples of how they may positively (and negatively) affect teaching, learning and assessment. Automatic video captioning, translation, video summarizing and highlight extraction, along with text-to-animation and voice to synthetic video all provide many new opportunities for pedagogical innovation and enhanced accessibility. In this emerging context – where AI systems can support the development of capabilities for learning as they become ‘smart companions’, ‘learning partners’ or ‘cognitive tools’ – metacognition and reflection gain importance over learning by rote. The resulting assemblages will entail a redistribution of agency among humans and machines. It will be essential to make informed decisions on the activities that we could ‘delegate’, and the ones we should retain, in order to maximize learning oppor-



tunities. Moreover, the report recognizes the need for critical evaluation of existing discourses regarding the impact of emerging technologies on education and learning, for example, to recognise their role in widening the digital divide and the risks of commercial interests unduly dominating the sector. The report highlights the importance of regulating technological innovation to allow diverse educational visions to thrive, also noting the need to connect industrial policy with theories of learning and education policy.

Open learner models that support the learners in reflecting and regulating their learning processes are particularly relevant from a learning theory perspective, and their importance will increase as agency becomes distributed between AI systems and humans. Self-reflection and self-regulation are essential for learning to happen, and better understanding of the development of agency is also important for AI governance models beyond education.

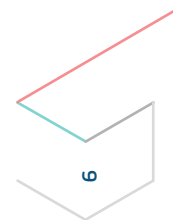
Likewise, the capability approach becomes relevant in new ways for educational policy when the emerging technologies are widely used for learning and teaching. In this context, the development of agency – what people are free to do and achieve in pursuit of goals and values they regard as important – can be viewed as the ultimate goal of education. Such a capability-based approach is expected to gain relevance in educational theories and policies as domain-specific and – more generally – epistemic skills become less important than they used to be. Overall, skills and competences are concepts that will need to be reconsidered in the light of emerging human-computer interaction entanglements.

The impact of emerging technologies on assessment, as a factor that heavily influences teaching and learning, deserves particular attention. Formative assessment

may increasingly gain prominence thanks to learning analytics developments, while AI will force a rethink about what should be assessed, how assessment data should be collected and used, and how new assessment practices might enhance learning. In any case, a key priority should be to avoid automating assessment practices that are no longer relevant in the new context.

All the emerging technologies and associated trends described in this report are profoundly interconnected with each other, while underpinned to a considerable extent by data and the increasing datafication of all aspects of society that characterises the postdigital age. The most significant policy challenge is how to best harness the potential of the new emerging socio-technical ecology of education without compromising the wellbeing of students and educators. AI must be trustworthy before it is fully embedded into the curriculum. Understanding the flows of personal data that result from the interaction between students and computer systems is an essential requirement for anyone making decisions regarding the introduction of emerging technologies in educational settings. Understanding the environmental impact of new technologies (e.g., in the energy-intensive training and use of AI systems) is equally important, allowing informed decisions to be taken about the extent to which they should be deployed in education and other areas of society. The digital transformation of education and society should not be accomplished at the expense of the green transition and sustainability.

The interplay – increasingly mediated by AI – between the digital ecosystem and the education sector will require an unprecedented interlinking of educational, digital, environmental, and industrial policy, especially the regulation around the structuring of markets and innovation processes.



# 1 Introduction

EU policymaking relies on scientific research and evidence-based recommendations to positively change society. Understanding current practices, behaviours, sentiments, opinions, and capabilities – just to mention a few key factors – is essential for the design of effective policies in any sector. It is equally important to examine the patterns that connect past and present socio-material dynamics. Apart from looking at the past and the present, the development of timely policy actions that can enhance the readiness for potential challenges and opportunities requires also imagining future scenarios. The future is yet to happen and is therefore by definition impossible to research empirically; but how potential futures come to be imagined and who takes part in such speculative endeavours actively shape the unfolding of events and contribute to defining the versions of the future that will eventually come to pass.

Speculative works on the futures of education tend to gravitate around digital technology (Facer, 2011; Ross, 2023; Selwyn et al., 2020). It is important to bear in mind that the visions of those behind the creation of technology heavily influence the way we, as a society, get to imagine what education might look like in the future. This means that the views, interests, and priorities of unprivileged populations are largely absent from dominant narratives and visions on the future of education. Such a lack of diversity ‘leads to narrow and unimaginative discussions about what AI ought to be, and the education issues that are deemed worthy of being addressed, and what specific social responsibilities are chosen above others’ (Selwyn, 2022, p. 628).

Over the last three decades, digital information and communication technologies – taking the form of software, data, algorithms, connectivity infrastructures, and computing devices of different shapes and sizes – have increasingly permeated all dimensions of society. Indeed, such a level of pervasiveness has rendered the term ‘digital’, and related prefixes such as ‘cyber-’ or ‘e-’, somehow meaningless as it is no longer possible to approach any fields of human activity without considering the very central role digital technologies play. The term ‘postdigital’ was already proposed before the end of the 20th century (Cascone, 2000; Pepperell & Punt, 2000), but it has gradually gained ground in the academic literature as a way of characterizing the current state of entanglement of technology and society. Present in a rather diverse range of disciplines, postdigital refers to ‘a state of becoming where the human and the digital are interacting, co-creating, and merging in ways that are beyond imagining’ (Ball and Savin-Baden, 2022, p. 754). However, instead of thinking of it as a chronological term that suggests that we now live ‘after the digital’, it is best understood as a critical attitude or philosophy concerned with the constitution, theoretical orientation, and consequences of the so-called digital world (Peters and Besley, 2019). The postdigital condition signals ‘our raising awareness of blurred and messy relationships between physics and biology, old and new media, humanism and posthumanism, knowledge capitalism and bio-informational capitalism’ (Jandrić et al., 2018, p. 896).

The concept of media and information ‘ecologies’ can also help us to refine our

understanding of the role that technology plays in mediating the relationships between humans and non-human actors and their environments. Adopting an ecological perspective in this sense entails looking at systems made of highly heterogeneous entities, including living beings as well as natural and socially constructed elements, all of them constantly coevolving in the course of continuous and non-teleological dynamics (Taffel 2019, Nardy & O'Day 2009). Technologies exist within the socio-material contexts in which they are invented, developed, and put into use. It is through situated practices that they become interesting, important, and relevant. Therefore, it is impossible to separate technological functionality from the human and social settings in which they are embedded. This takes the form, for example, of technological standardization, regulatory environments, economic arrangements, culturally shared expectations, both rational and unfounded fears, and current social practices.

Innovation becomes real only when it is used and appropriated in social practice (Tuomi, 2002). Technology is never neutral because every technology provides some affordances and enables some ways of using it, at the same time making other uses difficult or impossible (Miller, 2021). Technical affordances, however, are also underpinned by culture and thus influenced by norms, values, and current knowledge. The technological advances that we discuss below, therefore, need to be considered in a broader socio-technical context of development, driven by certain objectives, and uses. Technology is, by definition, instrumental and we need to ask what it is for<sup>3</sup> and whose interests it serves best. This in itself suggests that innovation and technological 'progress'

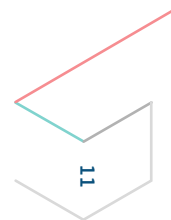
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3. Tuomi (2001) has argued before that technical change implies development only if it expands human capability for action that we have reason to value.

are inherently political topics that require a variety of viewpoints to be discussed and debated, always bearing in mind that they will benefit different populations unevenly.

In this report we address new emerging technological developments and trends, specifically emerging technical innovations and usage-related developments, with a focus on their educational implications and policy action. These include, most notably, important standardization initiatives that could shape technology use in the educational domain. Emerging technologies are constantly perceived as vectors of change with, presumably, the capacity to fix or neutralize the most pressing challenges faced by education. They are designed, sold, bought, and adopted with the hope that they will radically transform, for the better, learning within formal education and beyond. However, as highlighted by Facer & Selwyn (2021), the last four decades of research reveal that technologies alone have not been able to transform education, improve learning, resolve inequalities, or reduce teachers' workloads, while also showing that the unintended consequences that may result from technology adoption can be hardly predicted and that actual impact always depends on socio-technical contexts and factors.

Overall, the perceived potential of technologies tends to eclipse notions of what can be realistically expected based on facts and lessons learnt from the past about the actual implications of technology for society. In the case of science and education, while advances in information and communication technologies have certainly prompted a reconfiguration of the way we produce, share and access knowledge, excitement around new developments has often led to initial hyperbole and subsequent disappointment, for example, regarding radio



and TV (Buckingham, 2007) and computers (Cuban, 2001). The history of technology shows that it is impossible to accurately foresee the technologies of the future and their social uses, with abundant examples of predictions about technologies such as the telephone and the personal computer that ‘were little more accurate than flipping a coin’ (Nye, 2006: 211).

Still, there is value in attempting to anticipate the role that emerging socio-technical trends might play in education, as well as in trying to understand the ways in which they could foster or erode different visions for the future of education. In this regard, the formulation of relevant, effective, and timely educational policies in support of such visions requires drawing on history, examining current developments, and looking into possible futures that may result from the potential evolution of incipient trajectories.

Our current digital infrastructure rests on connectivity provided by the internet, and the massive transformation it is currently undergoing means that the overall digital landscape will soon look very different. Over the next ten years, this connectivity infrastructure will see fundamental changes with the introduction of 5G-advanced and 6G networks. In particular, 6G networks will connect physical, digital and social worlds in fundamentally new ways, with profound implications for learning, knowledge sharing, and knowledge use. This change is systemic: 6G, in combination with other significant developments and trends (e.g., the reduction of costs of computing capacity and edge computing) will bring together several key technologies that are now rapidly advancing in parallel, with limited convergence for now. These include immersive and augmented reality technologies, artificial intelligence (AI) and machine learning technologies, sensors, and blockchain. Per-

haps most importantly, data are becoming a crucial component that underpins both the development and the use of these emerging technologies. We introduce some key developments in these areas below for further discussion.

It has been suggested that data-driven AI is about to generate a socio-technical ‘Cambrian explosion’ in the coming years (Liang, 2023; Tuomi, 2022). This is because – even without much further technical development – generative AI and related foundation models are already having a major impact on many dimensions of society, including education and learning, work, and everyday life. Existing AI technologies can be used as tools in the AI development process itself, and the impact is cumulative. Such positive (i.e. amplifying) feedback is typical for those general-purpose technologies, such as steam power, electricity, and computers, which have become the key technologies of emerging techno-economic paradigms of the past. In AI, the development is extraordinarily fast, and social and economic consequences can already be observed. Because of this, the report also highlights the importance of understanding innovation dynamics in this area. As Blikstein et al. (2022) show in their empirical analysis of the futures of education, technology firms that develop AI for education spend considerable effort in redefining what intelligence, education, and learning are. These definitions are then fed back to educators and policymakers as images of the future, shaping their expectations and vision on the role that technology could and should play in education.

It is, therefore, essential to critically assess existing discourses about the impact of emerging technologies in education, so as to ensure that in Europe our priorities for an inclusive and high-quality education –

as defined in the Digital Education Action Plan – remain unchallenged. It is important that policymakers understand, for example, how commercial interests shape these discourses (Davies et al., 2021). In the case of data and AI, innovation dynamics can lead to natural monopolies unless regulation can shape the industry structure so that multiple visions of the future of education and technology can compete for prominence, making sure that ‘AI works for people and is a force for good in society’; as defined by the European approach to artificial intelligence.<sup>4</sup> Understanding critical perspectives from diverse stakeholders is vital (e.g. see Selwyn 2023 in relation to AI in education). Within this technological landscape, we can see how industrial policy becomes linked with theories of learning and education policy.

The report introduces key emerging trends, at different stages of development, from a technology-oriented point of view. The goal is to facilitate a rich and wide-ranging discussion, which could be complemented with further research drawing on methods from futures and foresight research.<sup>5</sup> It starts by looking at technology from a rather traditional engineering-oriented standpoint, to then focus on social impact and implications for education with the main aim being to offer relevant insights for policymaking in education.

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4. <https://digital-strategy.ec.europa.eu/en/policies/european-approach-artificial-intelligence>

5. On possible methodological approaches, see, for example, Miller & Tuomi (2022), Miller (2018), Tuomi (2019), and their references.

## 1.1 The emerging landscape of education

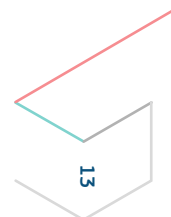
New technologies<sup>6</sup> are often viewed as solutions to widely recognized societal problems. In the case of education, they are actively proposed by different stakeholders as a ‘fix’ to pressing issues, for example the vision of AI helping teachers in marking student homework. Teachers spend many working hours in this task (OECD, 2019b), and it appears to be a natural opportunity for automation. Although the situation varies greatly across countries, teachers are often overloaded with administrative tasks and marking (Vuorikari et al., 2020). Policymakers in many countries are keen to find cost-effective ways of reducing these workloads in an attempt to make teaching more attractive and keep teachers teaching.

Many visions of the future of AI in education also claim that AI will radically transform formative assessment. For example, AI systems could provide continuous feedback for students and make real-time assessment and personalised or adaptive learning possible. In that vision of AI-supported learning, there remains little need to mark student homework.

Future visions of technology are rarely visions about any realistic or imaginable future. They are frequently based on past experiences. More often, they are predictions about the impact of new technological functionality while the rest of the world stays the same. For predictive models, this assumption of ‘other things being equal’ is a practical necessity. In real life it is, of course, fiction. Educational systems are composed of complex interdependent sys-

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6. In this report the term ‘new technologies’ is not determined by the date when a given technological innovation was first invented or made publicly available. Instead, it considers the extent to which group of users have found a meaningful way to integrate latent innovative opportunities in the current social practice (Tuomi, 2002).



tems, and their change requires a systemic approach. The adoption and appropriation of a new technology in education has a system-wide impact, much of which remains invisible when technology is understood as a solution to a given problem.

Computers have often been used to automate apparently well-defined tasks, such as ‘marking homework’, at the same time ‘hard-wiring’ work practices that reflect the constraints of the past. More generally, digital technologies can easily be used to scale-up pedagogic practices that resulted from the constraints of the past. Automation, by necessity, starts from a static view on a given system, assuming *ceteris paribus*, and successful automation makes system change difficult. To avoid being stuck with the needs of the past, we should, therefore, ask what the constraints of the future will be, and how emerging technologies could address the emerging opportunities.

For example, it is now clear that AI will have a profound impact on labour-market skill demand. A recent study by economists from Goldman Sachs (Briggs & Kodnani, 2023) estimated that roughly two-thirds of current jobs are exposed to some degree to AI automation, and that generative AI could provide a substitute for up to a quarter of current work. Similar findings were found by Sostero & Tolan (2022) in their classification of over 13,000 different skills required by employers, whereby several clusters that emerged were related to advance digital skills, including AI. For such skills, an associated 10.8% higher wage was offered. Many non-routine and knowledge-based work tasks will soon be supported by AI systems. Likewise, climate change and the decline in biodiversity pose large-scale challenges to humanity. The energy consumption of data centres and both the training and use of AI systems are becoming potentially impor-

tant sources of global warming. In addition to environmental consequences, AI is possibly amplifying societal and geographical divides while limiting sovereignty because computing capacity is unevenly distributed across the world (Crawford, 2021; OECD, 2022). For education, this means that those who have the material capacity to develop AI systems will be able to shape learning processes globally.

Lack of digital competence among teachers – and indeed the entire population – are seen as key challenges in Europe and beyond. These problems may, however, look very different as digitalization and developments in AI continue. At the same time – although causal links with digital media are still unclear (Odgers & Jensen, 2020) – depression, anxiety, and behavioural disorders are rapidly increasing among adolescents (Braghieri, Kevey & Makarin, 2022). Educational policymakers are now focusing on the development of social, emotional, and meta-cognitive competences (Chernyshenko et al. 2018, Council of the European Union, 2018, Sala, Punie, Garkov & Cabrera, 2020). Economically useful skills and knowledge are increasingly being developed outside formal education. In short, the **emerging landscape of learning and access to knowledge looks quite different from what it was when the existing institutions of education were formed** over the past centuries.

In addition, control and power are shifting across educational systems from some actors to others. What people learn and how they learn is increasingly shaped by commercial actors that remain largely outside the control of regional, national, and European policymakers. The EdTech industry actively influences formal education as it gets digitized. At the same time, digitization is making informal and non-formal learning in-

creasingly important for society, and educational institutions are looking for new sources of legitimization. Formal and non-formal education is increasingly putting learners in control of their learning, at the same time this might be seen as burdening individuals with responsibilities that used to belong to governments and the state (Biesta, 2015, p. 76).

Ensuring that education and training systems in Europe are fit for the digital age is a European Commission priority, set out in the Digital Education Action Plan 2021-2027. The plan is aimed at promoting high quality, inclusive and accessible digital education in Europe. The recent publication of the proposals for both the *Council Recommendation on the key enabling factors for successful digital education and training* and the *Council Recommendation on improving the provision of digital skills in education and training* addresses the growing importance of technology-mediated learning, a process which was accelerated by the sudden mainstreaming of remote learning during the COVID-19 pandemic. This unforeseen transition came with opportunities to modernize educational practices, but also with an exacerbation of pre-existing socio-economic gaps, the emergence of new challenges to equal participation in education and the uneven distribution of technological resources (Blaskó et al., 2022, Cachia et al., 2021).

Likewise, emerging technologies such as AI bring both opportunities and risks, prompting the need for a better understanding of the impact of technological innovations and for improved digital skills among educational stakeholders. In this respect, AI was addressed in the last update of the European digital competence framework for citizens: DigComp 2.2 (Vuorikari, 2022). A wide range of policy developments are relevant to the educational sector, reflecting Europe's commitment to enhancing digital

education and skills to nurture a digitally literate and competitive society. Most notably, these include A European approach to artificial intelligence<sup>7</sup>; the European strategy for data<sup>8</sup> (with the European Data Governance Act<sup>9</sup> and the Data Act<sup>10</sup>); the European skills agenda<sup>11</sup>; the proposal for an Artificial Intelligence Act, the Digital Services Act, and Digital Markets Act<sup>12</sup>; the *Ethical guidelines on the use of artificial intelligence and data in teaching and learning for educators*<sup>13</sup>; the Digital Decade policy programme<sup>14</sup>; as well as the proposed European digital identity framework<sup>15</sup>.

Below we focus on technology, but it is important to keep in mind the broader societal changes and historical trajectories that will keep shaping the education systems of the future. In this report we show how novel and emerging technologies already are (and could become even more) important for learning and education. It is, therefore, essential to understand these technologies better in order to assess the extent to which their use could redefine certain aspects of education and potentially help to address well-known existing problems. More interestingly, the emerging technologies discussed below will reveal their true potential as tools that will influence the future of education.

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7. <https://digital-strategy.ec.europa.eu/en/policies/european-approach-artificial-intelligence>
  8. <https://digital-strategy.ec.europa.eu/en/policies/strategy-data>
  9. <https://digital-strategy.ec.europa.eu/en/policies/data-governance-act>
  10. <https://digital-strategy.ec.europa.eu/en/policies/data-act>
  11. <https://ec.europa.eu/social/main.jsp?catId=1223&langId=en>
  12. <https://digital-strategy.ec.europa.eu/en/policies/digital-services-act-package>
  13. <https://op.europa.eu/en/publication-detail/-/publication/d81a0d54-5348-11ed-92ed-01aa75ed71a1/language-en>
  14. [https://commission.europa.eu/strategy-and-policy/priorities-2019-2024/europe-fit-digital-age/europes-digital-decade-digital-targets-2030\\_eneuropean](https://commission.europa.eu/strategy-and-policy/priorities-2019-2024/europe-fit-digital-age/europes-digital-decade-digital-targets-2030_eneuropean)
  15. [https://commission.europa.eu/strategy-and-policy/priorities-2019-2024/europe-fit-digital-age/european-digital-identity\\_en](https://commission.europa.eu/strategy-and-policy/priorities-2019-2024/europe-fit-digital-age/european-digital-identity_en)

## 1.2 Aim of the report

The report looks at emerging trends and technologies that are already or may in the future, contribute to the redefinition of educational practices, processes, and organizations. The aim of the report is to inform European policy stakeholders of important technological innovations and developments in the context of learning theory, in order to unpack their potential influence in teaching, learning and the organization of education. The scope of the report is limited to a series of digital technologies – currently at different stages of development and adoption – with high potential to be accompanied by significant societal transformations.

International institutions such as OECD (2022) and UNESCO (2021) have recently released reports on the impact of technology in the future of education. This report adds and complements existing work in this area by reviewing technological developments such as the emerging next generation internet, next generation virtual worlds, and AI technologies – in particular generative AI – that have the potential to disrupt the ways in which we understand and organize education.

Considering the extremely fast pace of technological innovation and evolution of the current media and information ecology, it is of the utmost importance to imagine a variety of possible alternative futures. In this regard, as a society we need to ensure that diverse voices are heard and to make sure that we go beyond industry-driven perspectives on the role that technology could and should play in education.

## 1.3 Methodology

There have been many attempts to imagine speculative scenarios for the future of educational institutions, with particular attention to teaching and learning. Technological trends, including digitalization, play a central part in these attempts. Some have relied on established scenario development methods (e.g., Baker & Smith, 2019; Facer & Sandford, 2010; OECD, 2020; Pelletier, 2021). Others have extracted key trends and used social science and design fiction in specific technology domains such as AI and robotics (e.g., Bai, Zawacki-Richter, et al., 2022; Cox, 2021; Selwyn et al., 2020), summarized the outcomes of expert opinions and stakeholder consultations (e.g., OECD, 2019a; Roschelle et al., 2020; UNESCO, 2021; Vuorikari et al., 2020), or presented more idiosyncratic visions of the future of education and learning based on expected technological and socio-technical developments (e.g., Pinkwart, 2016; Schiff, 2021; Tuomi, 2007; Unwin, 2019; Woolf et al., 2013). Future visions of educational technologies have also been extensively discussed in the context of science and technology studies, often critically highlighting the assumptions that underpin these visions (e.g., Selwyn, 2019; Williamson, 2017).

One way to study emerging technological trends would be to deconstruct the visions produced in such studies and analyse their technical requirements. For example, many visions of future digital education are based on the idea that instruction can be tailored and personalised for individual students using computer-based adaptive learning environments. Such a vision of personalised instruction generates clear design requirements for intelligent tutoring systems. They need to have a model of the knowledge domain, a similar model of student's knowledge state, a pedagogic model that moves

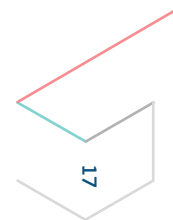


the student towards mastery, learning content that helps the student learn, and user interfaces that allow the system to interact with the student (Luckin et al., 2016). For each system component we could ask whether there are expected technical advances that could lead to breakthroughs that could realize the proposed vision. Indeed, some technology experts have suggested that personalised intelligent tutoring systems will soon revolutionize education (e.g., Lee & Qiufan, 2021).

Although this report is informed by these earlier discussions on the futures of education and learning, below we approach the future from a more idiosyncratic point of view. There have been few previous studies that integrate future-oriented technological analysis with educational theories. Below we try to do this basing our analysis on academic and grey literature and earlier research by the report authors, with the aim to highlight those aspects of emerging technologies that seem particularly relevant for education, learning, and education policy. In this sense, the present report aims to go beyond the state-of-the-art and facilitate richer discussions on the potential impact of emerging technologies in education in order to support long-term strategic thinking in education. At the same time, we have tried to validate the relevance of the report content by involving various experts during its development. Two workshops have been organised to discuss the draft report developed by the first author, and validate its ideas, structure, and content. For the workshops, we invited key innovative thinkers from three continents, able to cover the topics in the report and known for their high quality of research. The outcomes of these workshops have been integrated in our analysis. In addition, we have received feedback and comments from many educational experts who did not participate in the

workshops, but whose input is reflected in the referenced literature.

One starting assumption in this report is that technological developments will open up new possibilities with regard to the organisation and motivation of learning, at the same time generating new needs and societal objectives for education. The technical change that we see possible in the coming decade touches the foundations of society, its educational systems, and the processes of learning in ways that can appropriately be called disruptive. In simple terms, emerging technologies and associated social dynamics are expected to reconfigure some aspects of the educational field. The present report aims to explore this landscape, highlighting some of its salient features. As we explore a future that does not exist yet, we don't have empirical facts about it (Tuomi, 2012; 2019). In the spirit of abductive reasoning that generates hypotheses that reveal what evidence would be important, we simply try and interpret anticipated technical developments from the point of view of their implications for future learning and education. The aim is not to list all potentially important emerging technologies; instead, the objective is to help in locating and prioritizing trends that should be studied and further researched in more detail to gather evidence for policy development.



# 2 The next Internet

Sixth generation networks (6G) are expected to link the physical and the virtual worlds and enable and operate immersive technology-mediated experiences by the end of the decade. Although 6G provides similar wireless communication services as 5G, it also represents a conceptually new approach to digital networks. This expected technological change – which we describe as the ‘Next Internet’ – will have important social and cognitive consequences. The reason to highlight 6G and call the resulting socio-cognitive and technological infrastructure the Next Internet is that it will potentially generate a disruption that is in many ways like the one generated by the internet and the World Wide Web over the last three decades. The internet disrupted established forms of human communication and access to knowledge, impacting social interaction and cognition. On different levels, the impact of 6G will be similar, or even more profound. Beyond social relations, 6G will redefine our relationship with material reality and its time-space organization. It is not clear yet how this change should be conceptualized, but it is clear that it has direct relevance for learning and our current theories about how learning happens. To understand this disruption, it is useful to put the internet in its sociological context. We will return to this after first briefly reviewing the more technical aspects of 6G in the next section.

## 2.1 Towards 6G networks

A variety of use cases have been proposed for the 6G networks. Generic terms such as virtual worlds and extended reality are commonly used, although there are many

interpretations of what they would mean in practice. For 6G, relatively straightforward extensions of existing 5G use cases have been proposed. These include, for example, high quality real-time 3D meetings during high-speed train travel, remote surgical operations using virtual reality interaction, and more exotic applications such as holo-presence. From the point of view of learning theories, the core use case for 6G networks will, however, be ‘digital twins’. In the Next Internet, these will be digital and actionable representations of the physical world at different levels (from the whole Earth to the human body). Although the concept is not new, 6G networks enable the synchronization of the physical and the digital in qualitatively new ways.

In the Next Internet, the various functions of digital networks will be virtualized and implemented in a dynamically orchestrated network, where the control of the network itself will require very fast communication capabilities. Instead of centralized cloud platforms, much of the processing will occur at the edge of the network, close to the users, on what is being called ‘edge computing’. This will require dynamic allocation of data and processing across the network. The users will experience a very high-speed and low-latency network, where user devices can rely on many different situation-dependent access technologies. These are expected to use fast radio technologies, first at the 7-20GHz range and later towards millimetre wavelengths and terahertz frequencies. 6G networks will extensively use machine learning and AI, both in its foundational technologies – for example to beam directed radio signals from the antennas to the user location in a three-dimensional

space – and in predicting data needs and user movement. They will also to switch user devices across many different types of network access technologies as the user's data and processing requirements change.

In contrast to the 4G and 5G networks, which rely on cell towers where base stations connect the wireless network to the fixed networks and to the internet, 6G will move beyond the cellular network paradigm (Giordani et al., 2020). The very high speeds that the network is expected to provide require new wireless access technologies (Polese et al., 2021). These may include wide-spectrum access points embedded in homes, offices, and classrooms, optical communication using LED luminaries, and low- or zero-power devices that scavenge energy from available radio signals or other sources.

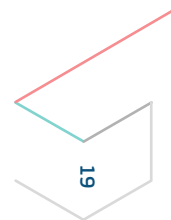
The vast increase in short-distance wireless access points implies that energy consumption, data security, and privacy are key design criteria for the 6G networks. Identity and identification infrastructures, as discussed later in this report, will therefore be integral elements in the Next Internet. A potentially important challenge will be the development of commercial quantum computing, which is expected to be available at the beginning of the next decade. This will make the current public-key encryption-based privacy and security approaches vulnerable. Although it is not clear how this challenge will be solved, semiconductor design tool providers are already starting to roll out chip architectures that increase the complexity of encryption algorithms so that they would be more resilient to quantum attacks over their expected lifetimes (Neustadter, 2022).

### 2.1.1 The emerging infrastructure of knowing, action, and learning

The material dimension of mediated interactions and information technologies have traditionally attracted much less attention than the content of messages. However, the physical settings in which actors are embedded, as well as the infrastructures available to them, play a key role in enabling or otherwise limiting their opportunities to access and share information. In relation to education, the term 'virtual' – as in Virtual Learning Environment or Virtual University – somehow implies that digital systems operate as realms for learning completely detached from the material world. Educational researchers writing at different times have confronted that myth (e.g., Gourlay, 2021; Robins & Webster, 2002) and the Covid-19 pandemic made more explicit the impact on education of socio-economic differences, as manifested by lack of access to dedicated spaces for study or the need to share devices with others.

In the Next Internet, the physical and the digital will become increasingly interconnected in more profound and complex ways. Beyond the obvious instrumental uses of new technical possibilities such as holographic presence and immersive simulations, the fusion of digital and physical creates what could be regarded as a new infrastructure for knowing and action. Interaction with the material environment has been a critical element in several influential learning theories.

To understand the difference between 6G and earlier communication technologies, it is important to note that spatially and temporally organized human-to-human interactions provide the foundation for social life. Recurring interactions make expectations possible and generate social habits, routines, and norms. Historically, these in-



interactions have required that people are physically present in a specific location at the same time. In Durkheim's (1933) classical description of the emergence of modern capitalist world, value-centric medieval villages transform into global networks of commerce as money enables transactions across geographies and cultures. Since Thorstein Hägerstrand's quantitative work in the 1950s on time geographies of social interaction, sociologists have increasingly emphasized the role of spatial structures as enablers and constraints in shaping societies and their practices (e.g., Crang & Thrift, 2000; Hillier & Hanson, 1984; Larsen et al., 2016). In terms of Castells (1996, pp. 410–411), 'space is the expression of society' and 'crystallized time' that provides the material support for time-sharing social practices. In a sociological interpretation, physical structures such as roads, bridges, airports, cities, and the architectures of dwellings and offices represent the outcomes of a long history of spatially and temporally organized human interactions. As such, they can benefit certain social groups while embodying biases and oppression dynamics against others.

The industrial-age organization of time and space was disrupted by the emergence of the internet. Very fast increases in optical network capacity at the turn of the 1990s (Hugill, 1999; Tuomi, 2002) created a new social infrastructure, and wireless networks have now further expanded outside the global hubs. The geography of this emerging 'cyberspace' was mapped by Castells in his landmark studies (Castells, 1989, 1996, 2001), and its characteristics have been extensively studied by sociologists, philosophers, cultural scholars, and philosophically oriented computer scientists over the last decades. Faster 5G networks will further solidify this interaction infrastructure, but 6G will be different. Whereas Castells focused on networks and the flows between the

hubs of information, technology, ideas, and organizational interactions, and their social consequences, 6G more directly connects cognition, space, and action. In this sense, we are moving towards a 'post-Castellsian' world.

In learning theories, this linkage between cognition, space and action is particularly prominent in those constructivist theories that emphasize practical action as a source of learning. John Dewey (1991), for example, argued that learning is rooted in concrete experience and requires practical experimentation with the material world. According to Dewey, learning starts when our habitual action does not lead to the anticipated outcomes and action is moved to an intellectual level. Similarly, Vygotsky (1986) argued that children learn by internalizing practical action. A central idea in Vygotskian learning theories is that action is mediated by practical tools that reflect the current historical level of technology, which can also become instruments of cognition (Bruner, 1986; Cole, 1996; Engeström, 1987; Leont'ev, 1978; Luria & Vygotsky, 1992). In this practical action, the physical characteristics of concrete objects both constrain and enable thought and its development. The interaction between the material and cognitive worlds was the starting point in Schön's (1987) analysis of learning processes, and also in Mead's (1967) symbolic interactionism.

Whereas the digital world until now has been mainly a representation and a reflection of social and material realities, human action and interaction are now becoming mediated by a real-time digital layer. Those individualistic variants of constructivism that understand knowledge development as the construction of mental or cognitive models of objective reality, assume that the learner is an observer of the world. These

are often inspired by the studies of Piaget, although Piaget himself argued that cognition and reality are mutually constructed (Furth, 1981). In social variants of constructivism, the learner, in turn, is a participant in a process of collective knowledge creation and building where systems of knowing are understood as fundamentally cultural products. For the Dewey, Piaget, and Vygotskian cultural-historical variants of constructivism, practical interaction with the physical world is the fundamental starting point for learning as well the source of meaning. Under this new perspective of framing learning, pedagogical approaches such as situated learning (Brown, Collins & Duguid, 1989) and problem-based learning (Barrows & Tamblyn, 1980) have emerged, prompting educators to shift their teaching to make learning more relevant for students by creating learning in realistic or simulated environments (Herrington, Reeves, & Oliver (2007). While the social transformation discussed by Castells focused on the new time-space organization of social interactions, in the context of such action-oriented theories of knowledge creation and learning, the technical characteristics of 6G networks imply a reorganization at the deeper level of human cognition and action.

The ‘sensorization’ of the network means that spatiality and body become important elements in the digital future. This opens up, for example, new lines of research on extended (Gibson, 1977; Vygotsky & Luria, 1994), embodied (Dourish, 2001a; Varela et al., 1991), situated (Suchman, 1987), and distributed (Hutchins, 1995; Pea, 1985; Salomon, 1993) cognition, with potential implications for theories of learning and pedagogic practice.

## 2.2 Immersive technologies: Extended reality, holograms and virtual worlds

Extended Reality (XR) is a term commonly used to describe a set of technologies that augment or extend human perception of the real world. These technologies include Augmented Reality (AR), Virtual Reality (VR), and Mixed Reality (MR) (Chang et al., 2022; Kaplan et al., 2021). Although the idea of using extended reality and immersive virtual worlds for learning and education is an old one,<sup>16</sup> and their use in education has been explored from different aspects (Vourikari et al., 2020), technical requirements for XR have limited their development. Fast networks, such as 5G and Wi-Fi 6 are now unlocking some key constraints, and the emerging Next Internet, combined with AI-supported content production tools, can also be expected to lead to expansion of XR in education.

VR is a fully artificial environment that a user can interact with. Early examples of VR include virtual game worlds and platforms such as Second Life and, more recently, Minecraft and Roblox, but often the term is understood to imply immersive experience that requires specialized VR headsets. Augmented Reality, in contrast, involves superimposing digital content onto the real world. Mixed Reality, in turn, synchronizes the digital and physical worlds, and combines actionable computer-generated objects in an augmented world. With fast networks and processing, these actionable digital objects can be directly linked with physical artefacts, blurring the boundaries between the representation and the represented.

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16. Some examples were discussed, e.g., in Tuomi (2005, Chapter 6).

Over the last decade, there have been great expectations about the transformative impact of XR. For example, Meta has been spending about \$10-12 billion annually on its XR initiatives, and about \$50 billion by the end of 2022, against \$6 billion in revenue since 2019 (Ball, 2023). The global AR market was estimated to be \$25 billion in 2021, with a compound annual growth rate of over 40 per cent from 2022 to 2030.<sup>17</sup> The developers of XR technology have, however, realized that immersive XR has surprisingly demanding technical requirements that may delay the wide adoption of XR for several years, particularly for consumer use.<sup>18</sup>

AR can be experienced through a smartphone camera that provides a 'magic window' or 'portal' to the augmented reality or using a specialized AR headset for a more immersive experience. Detached display devices, such as mobile phones, can use their sensors to track the device pose using three degrees of freedom and provide a monoscope simulation of a 3D world. Low-cost stereoscopic implementations have been built using 'cardboard boxes' that imitate the classic View-Master device with a standard mobile phone. This approach is used, for example, in Google's Cardboard.<sup>19</sup>

In contrast to XR cardboard boxes that can be purchased for a few euros, high-quality head mounted devices adjust the perceived world in six degrees of freedom,<sup>20</sup> adapting both to the user's movements and to rota-

tional head movements for an immersive experience with three-dimensional surround sound. It can be expected that headset tracking will be increasingly common in the future when low-cost AI processors can be used to map the environment. With these advanced technologies, not only are user movements tracked by fixed 'base stations', but 'inside-out-tracking' is also possible, where the headset itself tracks the user.

One of the areas where XR has been successfully used is in applications that allow students to explore human and animal anatomy and practice surgical procedures. XR has also been used to enable immersive visits to historical periods and outer space, for interactive language learning, and the visualization of mathematical functions (XRA, 2022). XR simulations have also been applied, for example, for employee training for dangerous work tasks in oil rigs and supermarkets, and for training professional athletes (Bailenson, 2018).

XR is also used in many industrial and manufacturing settings. In the health sector, XR provides a training environment that adds value when compared to observation-based ways of acquiring procedural knowledge. For example, in 2020, surgeons at the John Hopkins University School of Medicine performed spinal fusion for a patient and removed a tumour from the spine of another patient using AR. In these operations the headset overlaid the patient's internal anatomy (such as bones and other tissue), recorded using CT scans with a see-through image.<sup>21</sup> Adoption of XR in health education can have a significant impact on the quality of education in providing simulated environments for training and practicing, skill assessment, and procedural knowledge acquisition (Iop, El-Hajj, Gharios et al., 2022).

17. <https://www.grandviewresearch.com/industry-analysis/augmented-reality-market>

18. These include very high-density displays, processing power that is needed to manage XR applications and user and environment monitoring, as well as the need for light-weight power sources. It is commonly expected, for example, that VR headsets may require 12 cameras to track the user's eyes, fingers, and location. Related technical and economic trends and remaining challenges are analyzed in detail in Ball (2023).

19. <https://arvr.google.com/cardboard/get-cardboard/>

20. This refers to the specific number of axes that body can move in a three-dimensional space.

21. <https://www.hopkinsmedicine.org/news/articles/johns-hopkins-performs-its-first-augmented-reality-surgeries-in-patients>

In more consumer-oriented applications, XR is also becoming widely used in gaming and entertainment, e-commerce, and retail.

Although consumer headsets have mainly been marketed for VR gaming, it is expected that adding video feed-through will make them usable also for AR and MR.<sup>22</sup> High-quality headsets are still relatively expensive, with a typical consumer setup costing several hundred euros and a high-performance PC or a game station. More importantly, it has been expensive to develop content for XR. It can be expected that generative AI tools will soon disrupt the economics of XR content creation, including for educational applications.

The size, weight, and cost of XR headsets will most likely diminish quickly in the coming years. Beyond the bulkier headsets, there have been several attempts to commercialize light-weight AR eyeglasses. The first wireless AR contact lens was demonstrated in 2022, although its development was discontinued soon after.<sup>23</sup> The state-of-the-art now includes light-weight stereoscopic full-colour augmented reality glasses that use micro-LED optical waveguide displays. State-of-the-art glasses support, for example, GPS-based mapping of the environment, gesture recognition, and real-time translation when speaking face-to-face by showing translated subtitles on its screen.<sup>24</sup>

A variant of immersive technologies is the hologram. Three-dimensional holograms have been proposed for educational uses

at least since the early 1990s (e.g., Ghuloum, 2010; Yoo et al., 2022). In recent years, holograms have been used to put deceased superstars on stage, including Whitney Houston, Maria Callas, Buddy Holly, Ronnie James Dio, and Glen Gould. Although the technology used has often been based on image projection, there have also been experiments with real 3D holograms. A well-known early example was the holographic news report in CNN's 2008 Wolf Blitzer -anchored news program, where a reporter was 'beamed in' to the studio floor to comment on the results of the U.S. presidential elections. Commercial holography devices are now marketed as replacements for online meetings, for e-commerce, hospitality, and for education. These include the life-size communication platform offered by Proto Inc.<sup>25</sup> and Solid Light technology from Light Field Lab.<sup>26</sup> The latter uses a similar electromagnetic beaming approach to 6G antennas.

The impact of VR and, more generally XR in educational settings has been studied in many small-scale research projects (e.g., Pellas et al., 2021; Yiannoutsou et al., 2021), with various studies conducted in the medical field, but the rapid advances in technology make generalizations about learning outcomes still difficult. Another limitation is the geographical distribution of such advanced technology. Most research in this field, for instance in medical education, is conducted in Canada and USA, where most XR systems employed in the studies are devised (Iop et al, 2022). Bailenson (2018) has suggested that XR applications can be particularly valuable in relation to learning situations characterized by the DICE principle (Dangerous, Impossible, Counterproductive, Expensive). According to

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22. <https://www.linkedin.com/pulse/23-augmented-reality-trends-keep-eye-2023-tom-emrich>

23. Due to tight capital markets in 2022 and the 'yet-to-be proven market potential', the developer of the AI contact lens, Mojo Vision, decided in 2023 to discontinue its work on this technology and focus on Micro-LED technology <https://www.mojo.vision/news/a-new-direction>

24. <https://www.tcl.com/global/en/news/tcl-unveils-groundbreaking-augmented-reality-glasses-at-ces-2023>

25. <https://protohologram.com/about/>

26. <https://www.lightfieldlab.com/>

this, XR could replace experiences that are difficult, impossible, or non-desirable in the real world. In educational settings such experiences are often excluded by design. This suggests that XR could expand the space of learning, instead of replacing already existing learning activities. Based on a review of literature on neurosurgical education, Iop et al., 2022 highlight the relevance of using XR systems for skills assessment, whereby a system could be developed to enable self-assessment or evaluation by experience neurosurgeons. Likewise, those forms of simulations will be particularly relevant to the vocational education and training (VET) sector, particularly work-based learning. For example, by having a simulated environment to learn how to operate dangerous or hazardous machines, as close as reality as possible but without real safety risks. Such innovations are part of the main focus of a council recommendation on improvement of the provision of digital skills to the Member States that was published in April 2023 (European Commission, 2023b).

On the other hand, it is important to bear in mind that the simulation of dangerous, impossible, and counterproductive experiences can also be psychologically harmful, in particular, for children and adolescents. For example, it may be educational to have immersive experience of learning history by burning Rome as Nero or to understand the impact of schoolyard bullying through a XR game, but this also raises many ethical questions. The ethics of XR use will, therefore, be an important topic also in educational settings. XR devices and applications will create vast amounts of fine-grained data on user behaviour and environment, and there are already indications that privacy and the ethics of educational XR need to be addressed soon (e.g., Christopoulos et al., 2021; Steele et al., 2020).

Virtual worlds have often been used to refer to an immersive virtual place and the next frontier for gaming, social media, and advertising (Wunderman Thompson, 2022). In the context of futures of learning, virtual worlds are perhaps best understood as a form of mixed reality. As discussed above, its true impact will be seen when the physical, social, and digital worlds become inter-linked in real time. Although there has been much hype around the term, this integration of digital with the social and physical generates some new foundations for the social world. Existing social, economic, or cognitive theories have little to say about developments in this emerging universe. However, the emergence of new generation virtual worlds and so-called metaverses comes with important societal implications, opportunities, and challenges (Hupont et al., 2023).

### 2.3 Digital credentials and identifiers

Credentialing and certification are important social functions of education (Biesta, 2010). In many professions, credentials and educational certificates are required for entry to an occupation or for performing specific job tasks. Such credentials are often important constituents of systemic trust which, for example, allow us to expect that people in the cockpit know how to fly the plane, or that an electrician can connect an electric oven safely. In other words, paper qualifications have traditionally worked as a proof that someone has the competences defined by the intended learning outcomes established in the curriculum of a given educational programme or level.

Digital technology is reconfiguring the way educational institutions issue credentials in diverse ways. For example, by supplementing or replacing paper certificates with elec-



tronic versions, verification becomes easier to key stakeholders such as employers or other educational institutions for further studies. At the same time, while credentials were traditionally issued to students only after completing an entire academic programme, there is now a growing level of granularity in certification practices. In this regard, micro-credentials (e.g. open badges) have proliferated as a way of evidencing skills, the completion of short courses or modules, as well as other achievements in formal and non-formal learning, especially in higher education and VET.

Partly because of the rapid technical change and the possibility to generate skill definitions from online job announcements using natural language processing, it is now common to generate increasingly detailed lists of skills that could be verified and validated. Micro-credentials have emerged as a natural answer to the need to manage information about such detailed skills. In theory, such skill lists can provide useful views on labour market skill gaps and information on skill development needs, albeit inherent to some biases towards more professional occupations (Sostero & Fernández-Macias, 2021). Such skill lists and taxonomies are now widely used around the world for labour market analysis, educational guidance, and in educational planning.<sup>27</sup>

### 2.3.1 Micro-credentials

In recent years, micro-credentials have been widely implemented for many different purposes, with the support of governments and intergovernmental organization (OECD, 2023). The interest in micro-credentials at least partly reflects ongoing technological

change that has reduced the labour-market relevance of traditional educational degrees (European Commission, 2021c; OECD, 2021; Oliver, 2022; van der Hijden & Martin, 2023). Micro-credentials enable flexible learning paths and the recognition of prior learning, at the same time facilitating broad access to short courses that can close labour market skill gaps (Council of the European Union, 2022a). They can be beneficial as standalone certifications, or as a way to complement other established programmes for greater employability, but also to improve lifelong learning (Orr et al., 2020).

Many digital-era skills are related to new tools and technologies that often have short lifetimes or that require people to be able and ready to upskill or reskill at a fast pace. This has led to an interest in packaging training and education in short courses and personalised segments of ‘microlearning’ that could be accumulated to cover wider areas of expertise. The premise is that these alternative credentials could then be used to address labour market needs, and to help individuals in forming meaningful lifelong learning paths.

Micro-credentials can record such learning paths for three different purposes. Many current ‘micro-credentials’ address regulatory requirements. For example, a ‘hygiene passport’ may be required from restaurant workers that certify that they are able to handle food items. A plumber may not be allowed to solder copper pipes without a firework permit. Similarly, to legally drive a car on a public road requires the driver to have a driver’s license that certifies that the driver knows traffic signs and rules and has verified skills in handling the car in practical settings. Such micro-credentials are essentially permits. They have high labour market value as they open access to restricted jobs.

27. This approach has been used, for example, in Cedefop’s Skills-OVATE system that analyzes online job advertisements. Skills-OVATE is now jointly developed by Cedefop and Eurostat as part of the Web Intelligence Hub. A detailed review on existing initiatives in this area can be found (in Finnish) in Tuomi et al. (2021).

Micro-credentials are also widely used as a signalling mechanism in the labour market. For example, many technology providers offer certificates that aim to prove that a person is familiar with that technology. Signals relevant for the labour market tend to be both domain and technology specific. They can, for instance, show that a person knows how to form SQL queries, is able to waterproof a renovated bathroom with the products of a specific vendor, or knows how to operate a particular machine. While there is still limited evidence on the perceived value of micro-credentials, they play an increasingly relevant role in the context of growing competency-based recruitment and the challenges of traditional talent development (Gauthier, 2020; Hollands, 2023, OECD, 2023). Micro-credentials are often viewed as a tool to address labour-market skill gaps and as a mechanism that could guide job seekers to complementary training and education that improves their employability, as they can help employers in the process of filtering and sorting potential applicants.

Micro-credentials are also used in social representation, self-reflection, and professional identity construction. Open badges, for example, are a means of building one's online identity. They are often literally badges and emblems that showcase achievements and signal membership of professional associations. In lifelong learning, micro-credentials can represent progress towards self-imposed objectives. The organizers of massive open online courses (MOOCs), for example, often make effort visible by providing a badge for successful participants.

As micro-credentials are assumed to reflect knowledge, skills, and competences, the dynamics of competences underpinning these three types of micro-credentials suggest

that their implementation may need different infrastructures that can also ensure quality assurance and standardisation in the way micro-credentials are recognised. This remains a complex issue because there are still limited digital solutions that are able to validate, recognise and store micro-credentials. In addition, some technical skills are directly associated with specific technologies and tend to become obsolete fast and the content of skills changes rapidly.

The fast-paced obsolescence of skill definitions could pose a significant challenge to human resource departments. Large organizations are particularly vulnerable to this issue, as they may well keep skill terms in their competence-management systems for decades, even when their content substantially changes. In general, the apparent stability of skill definitions in many skill taxonomies can be viewed as an artefact generated by the taxonomy itself (Bowker & Star, 1999). This decoupling of skill definitions from actual work tasks may limit the value of micro-credentials in certifying labour-market relevant skills. However, one of the benefits of digital credentials is that the metadata they contain may provide information to evidence skills and other achievements.

Online job advertisements often include long lists of expected skills and accumulated experience that are used to generate skill taxonomies. Skill definitions extracted from online job advertisements may easily become reified. Such skills definitions might also be used as the basis for micro-credentialing. It is not clear how important micro-credentials would be in the actual hiring process. However, it is widely known that machine learning systems are already extensively being used to sort applicants, and that HR professionals believe that AI will radically change recruiting processes (Fatemi, 2019;

Hunkenschroer & Luetge, 2022). Moreover, further research might be needed to explore the extent to which the description of tasks and skills in job descriptions reflect the real needs of employers.

As the development and use of machine learning systems requires data, it will be natural to think that detailed data on certified knowledge and skills would be useful and necessary. The epistemological assumptions that underpin such thinking, however, are complex and it is important to make them explicit.<sup>28</sup> The most requested competences in job advertisements include ‘soft skills’ such as ‘team working’, ‘problem-solving’, and ‘communication’ skills that are very different from domain specific technical skills and knowledge typically learned at educational institutions.

### 2.3.2 Verifiable credentials

According to the World Wide Web Consortium (W3C), a verifiable claim is a qualification, achievement, quality, or piece of information about an entity’s background such as a name, government ID, payment provider, home address, or university degree (Sporny et al., 2022). The W3C Verifiable Credentials standard defines methods to issue, assert, verify, store and move, retrieve and revoke claims. In their use cases (Otto et al., 2019), W3C highlights four use cases for education: digital transcripts of student grades and competences issued by an educational institution; proof of student identity for high-stakes tests; student-controlled storing of accumulated credentials; and identification of student identity in online learning systems such as massive open online courses (MOOCs).

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28. These epistemological assumptions have been extensively discussed in organizational knowledge management and knowledge creation literature (Brown & Duguid, 2001; Nonaka, 1994; Tuomi, 1999; von Krogh et al., 2000).

Over the last decade, blockchain has become an established technology in different sectors, prompting interest also for its possible applications in education (Bosch et al., 2022; Grech et al., 2022; Smolenski, 2021; Camilleri et al., 2017). Although from a technical point of view blockchains are just a way to implement distributed digital ledgers using public-key encryption, they are often claimed to have the potential to revolutionize learning and education. According to such views, they could transform individual skills development and life-long learning, provide new models for funding educational institutions, and, for example, allow billions of potential students in less developed countries to gain low-cost access to learning (Tapscott & Kaplan, 2019). Nevertheless, it can be argued that the education sector has not found blockchain as a useful response to their most pressing needs and there are indeed several challenges to its adoption beyond pilots; including philosophical, practical and legal challenges (Park, 2021; Steiu, 2020).

The idea that blockchains could in the future be used to register micro-credentials is conceptually founded on the view that reliable information about increasingly specific skills can be upgraded and presented, for example, to future employers. The link of cultural factors to blockchain technology with concepts such as ‘democracy’, ‘lack of central authorities’, ‘data self-sovereignty’, ‘decentralised autonomous organizations’, and the idea that individuals could control their identities, is a partial explanation why such technologies have such a strong presence in the public discourse, especially in education. From a sociological point of view, the proposed models of democracy, authority, and identity deserve further elaboration. From an educational point of view, the technical and standardization work on verifiable credentials (VC) and decentralised



identifiers (DIDs) will, however, be important in the coming years.

The EU has been among the leading developers of large-scale infrastructures in this area, with the European Blockchain Services Infrastructure (EBSI) and the Regulation on electronic identification and trust services<sup>29</sup> for electronic transactions in the internal market (eIDAS). EBSI is also used by the Digital Credentials for Europe (DC4EU) pilot<sup>30</sup> for the European digital wallet, which 'will be available to EU citizens, residents, and businesses who want to identify themselves or provide confirmation of certain personal information'.<sup>31</sup> The digital wallet will, for example, support electronic attestations of attributes such as the existence of educational diplomas and professional certificates. The European Digital Credentials for learning (EDC) infrastructure,<sup>32</sup> which underpins Europass,<sup>33</sup> already offers a standard for tamper-evident electronic documents that allows providers of credentials to describe and show the achieved learning outcomes (knowledge, skills) of learners.

Although blockchains have been claimed to be extremely relevant to education, the full educational potential of blockchain technology remains to be fully realized. There have been attempts to build new blockchain-based 'educational ecosystems' and 'blockchain universities' but so far these initiatives have not been successful. Typical expected benefits in research literature on educational uses of blockchains include improved security, better control of data access, enhanced accountability and trans-

parency, enhanced trust, student authentication, and cost savings (Alammary et al., 2019). At present, the most frequent application types are certification and validation processes and authentication of self-sovereign digital ID services (Bosch et al., 2022).

Several common use-case scenarios, however, have been proposed. Crech et al. (2022; 2017), for example, list eight scenarios for blockchains in education. These include the permanent secure storage of educational certificates, automatic recognition and transfer of credits, student identification, and verification of multi-step accreditation. Smolenski (2021) suggests that the main impact of blockchain technology will be as a new credentialing system, with the potential to eliminate records fraud, streamline and reduce the costs of record sharing and verification, and reducing institutional risk by returning the control of personal data to individuals. While relevant to many administrative processes central to education, those developments seem to be rather far from the main pedagogical aspects that shape teaching, learning and even assessment. In this regard, it is not clear whether blockchain is the most suitable way of addressing the needs of educational institutions, although its potential value in relation to interoperability, mobility or security, to mention a few aspects, cannot be ignored. At the same time, it would be irresponsible to ignore the heavy ecological footprint associated with blockchain (Schinckus, 2021).

The possibility to use blockchains to store fine-grained information on micro-credentials may allow individuals to own and control their personal learning histories. However, the impact of these technologies is still limited and is not necessarily the most optimal way for addressing the needs of the educational sector. It is important that such technology innovations are grounded in theories of learning and skill development. As learning is fundamentally about

29. [http://eur-lex.europa.eu/legal-content/EN/TXT/?uri=uriserv:O-JL\\_2014.257.01.0073.01.ENG](http://eur-lex.europa.eu/legal-content/EN/TXT/?uri=uriserv:O-JL_2014.257.01.0073.01.ENG)

30. <https://www.dc4eu.eu/>

31. [https://commission.europa.eu/strategy-and-policy/priorities-2019-2024/europe-fit-digital-age/european-digital-identity\\_en](https://commission.europa.eu/strategy-and-policy/priorities-2019-2024/europe-fit-digital-age/european-digital-identity_en)

32. [https://year-of-skills.europa.eu/news/new-version-european-digital-credential-learning-infrastructure-released-2023-07-26\\_en](https://year-of-skills.europa.eu/news/new-version-european-digital-credential-learning-infrastructure-released-2023-07-26_en)

33. <https://europa.eu/europass>

change, the dynamics of micro-credentials is a highly important topic in this learning-theoretical context.

In many blockchain-oriented visions of the future of education, technology is understood to enable fine-grained management of skills and related certificates. In the context of learning theories, such an atomistic model of skills and competences looks inadequately developed. As there are many ongoing national, EU-level, and international initiatives in this area, it would be important to gain better understanding of the potential of micro-credentials in certifying competences and learning in different application areas and also to identify which skills lend themselves better to their use. Also, a good understanding of the data infrastructures that are needed to support such developments is important. For such an understanding we must clarify the nature of various types of skills and perhaps also anticipate the impact of emerging technologies on their development. We will return to this topic in the context of AI-enabled learning later in this report.

### 2.3.3 Decentralised identifiers

While it is easy to understand potential uses of verified credentials in education, perhaps a more fundamental and disruptive specification has been developed for decentralised identifiers, or DIDs.

DIDs generalize the core idea of the World-Wide Web. The current web relies on universal resource identifiers (URIs) that point to documents and computational resources. A decentralised identifier, in contrast, can point to anything, including persons, organizations, material objects, or concepts. For each DID, there is an associated 'DID document' that stores keys and data that can be used to identify the 'subject' referenced by the DID, as well as verify any claims about

it. DIDs are 'decentralised' because the DID documents are stored in trusted distributed data storages, for example using blockchains.

DIDs are a core technology of the Next Internet. They will fuse cognitive, social, and material dimensions in a homogeneous digital universe. As noted above, this will make the digital realm actionable in fundamentally novel ways. Although this emerging universe is often called metaverse or virtual worlds, suggesting that it would be a parallel description of our everyday reality, the combination of Internet of Things (IoT) and the social world will be something that sociological or educational thinkers have not seen before. Although it is easy to imagine ways in which immersive social worlds can be used in existing practices of instruction, more philosophical and conceptual questions like what we actually mean by knowing and learning in such environments, will become relevant (Dourish, 2001a; Furth, 1981; Nonaka et al., 2008; Piaget, 1970; Rosen, 1998). A practical consequence is that as their epistemological foundations are reconsidered, many concepts that underpin education may, at least partially, become obsolete.

It is important to note that the emerging technologies are not just 'applied' to solve existing problems or to address expected challenges. There are good reasons to expect that these technologies change the foundations of societies, including the ways in which they produce and use knowledge. This is nothing new. Leading social theorists have highlighted the importance of new communication technologies, such as the printing press (Habermas, 1989; McLuhan, 1962), information technologies (Giddens, 1984; Thompson, 1995; Webster, 1995), and communication networks (Castells, 1996) for social life. The linking of the material, social and cognitive realities through



data can also be expected to require new concepts for understanding how policies should be developed for this emerging world. Whereas many of the earlier classical discussions focused on social interaction and communication, DIDs go beyond communication by linking material objects to this emerging network of interaction. ‘Computational embodiment’, in this sense, means ‘a presence and participation in the world, real-time and real-space, here and now’ (Dourish, 2001b).

While the above considerations may lead to conceptual discussions that may be unfamiliar to some technology developers, blockchains also have some more immediate technical and regulatory challenges that will have implications for their use. For example, core blockchain design objectives challenge key assumptions of European data protection law, such as data minimization, purpose limitation, and right to be forgotten (Finck, 2019). It is not clear whether certificates that are stored in blockchains should be considered personal data. It is also not obvious how the requirement that under specific circumstances data must be amended or erased could be interpreted in the context of blockchains, where such changes are impossible by design. As one of the claimed benefits of blockchains is that they cannot be controlled by any single actor, it is difficult to find a data controller as required by the GDPR. Due to their distributed nature, the updating of blockchains also becomes very slow if the number of transactions to be recorded grows. Also, the exorbitant amounts of energy needed to keep the distributed trust mechanisms operating is a well-known challenge for the

green transition.<sup>34</sup> Beyond the more foundational conceptual problems related to the potential benefits of blockchains, micro-credentials, and decentralised identifiers, there are also very concrete engineering problems that may limit the use of these technologies.

One such technical problem is the possibility that blockchain technologies will become obsolete in the coming decade as quantum computing becomes able to disrupt the trust infrastructure that makes blockchains possible.

## 2.4 Post-quantum cryptography and zero-knowledge proofs

Over the next decade, blockchain technologies need to implement post-quantum cryptography (PQC). Existing blockchain architectures rely on public-key cryptography that is expected to become obsolete in the next 10-15 years. At present, it is not known how blockchain-based trust platforms will adapt to the post-quantum era, or how the existing transactions and contracts recorded in them can remain immutable. PQC methods and communication protocols such as Quantum secure layer (QSL) are, therefore, actively studied at present.<sup>35</sup>

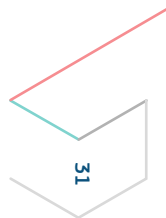
To some extent, these challenges are engineering problems, and problems with the interpretation and adaptation of law, but

34. The Cambridge Bitcoin Electricity Consumption index estimates the annual Bitcoin power demand to be at 115 TWh and at 13 GW at the time of writing: <https://ccaf.io/cbeci/index>. The upcoming proof-of-stake trust mechanism planned for the Ethereum will consume much less energy. The Bitcoin blockchain can make about four transactions per second, using 707 kWh per transaction. This is about 11 times that of the current Ethereum.

35. See, for example <https://www.nist.gov/news-events/news/2020/07/nists-post-quantum-cryptography-program-enters-selection-round> and (Beullens et al., 2021).

they also suggest that some earlier optimistic visions of the forthcoming blockchain revolution may lack important detail. In general, it will be important to integrate sociological, legal, ethical, developmental, and cybersecurity knowledge in assessing the impact of technologies such as verified credentials and decentralized identifiers in the educational domain.

If educational certificates are stored in a permissioned blockchain, where the access can be linked with separate contractual terms of use, ‘zero-knowledge proofs’ could address some regulatory and privacy-related challenges. Zero-knowledge proofs (ZKPs) enable data-minimization and selective disclosure (Goldwasser et al., 1989). Zero-knowledge methods allow the data subject to choose which attributes to reveal and which attributes to withhold on a case-by-case basis. The approach uses predicate proofs that allow the verifier to ask true-or-false questions, for example whether the person is over the age of 18 or whether the person has a given professional certificate. In the context of the EU digital wallet (European Commission, 2023c), such zero-knowledge proofs are known as ‘attestable attributes’. At present, there are only relatively generic use cases developed in this area, including the possibility to upload digital diploma attestations and professional qualifications in a personal wallet. Whether a similar approach could be used for micro-credentials remains a topic for further research and policy development.



# 3 Data

Specifications such as DIDs will enable the Next Internet, but perhaps the most important technology for education in the next years will be data. One of the most important consequences of the increasing pervasiveness of computerization and informatics has been an exponential growth in the amount of data generated as a by-product of our daily activities. As we engage with online services and apps, whether actively or simply by carrying with us our smartphones, we leave behind valuable traces of data that are the basis of the current economic system (Cohen, 2019; Zuboff, 2019). Moreover, as we transit through our increasingly monitored surroundings, large amounts of data are also generated upon us, and self-tracking enabled by wearable devices has become a common activity (Lupton et al., 2018). Data is the cornerstone of the current media and information ecology and the amount of data generated, stored, and processed is expected to keep growing at an even faster pace, partly due to the growth of IoT.

Data are used to train data-driven AI, for learning analytics, and for research on learning. Many arising concerns in educational settings are related to the production, use, and dissemination of data (Day, 2021; Livingstone & Pothong, 2022; Williamson, 2017). We are generating enormous amounts of data while using digital technologies.

Privacy and ethics of data use are key political priorities in Europe. Moreover, access to high-quality data on learning and education will be a key factor for research and development of AI applications in and for education (McNamara, 2023).

The EU is a global front-runner in data regulation and governance, as shown by the General Data Protection Regulation (GDPR) and the ambitious European Strategy for Data that includes the already adopted Data Governance Act aimed at improving trust between different actors in the data economy and the proposed Data Act aimed at improving the fairness of the data sharing. Large-scale data on education and learning will be at the core of the knowledge society transformation. Such data extend beyond records on learning outcomes, credentials, and statistical data. Digital learning environments also enable the collection of data on learning itself. This is something that has been impossible until recently, except in small-scale research. Many educational collaborative platforms and learning environments used in Europe belong to non-European companies and this cannot be ignored.

In recent years, detailed data on learning processes has increasingly been accumulated by the providers of digital learning platforms. Much debate has therefore concentrated on potential problems associated with the uncontrolled flows of data to commercial actors, and the more conceptual need to critically assess the benefits and harms of ‘datafication’ of education (e.g., Lupton & Williamson, 2017). Among other things, this has generated debates on the role of commercial interests in the development of educational practices and policies (e.g., Perrotta et al., 2021; Perrotta & Selwyn, 2020). Datafication and commercialization of education have been widely discussed in recent years but deserve further attention from all key stakeholders in the sector in the light of new regulatory frameworks.



### 3.1 Implications of data spaces for education and learning

Datafication can, however, also be viewed as an engineering or an industry policy problem. If large-scale detailed data on learning processes and outcomes is important for the development of new pedagogical approaches, learning technologies, and education policy, we need to ask what data are needed for this, and how these data can be made available. Much of these data already flow on the global information networks, and the emerging digital technologies will rapidly increase the amount of data that could be used to develop education and educational services. As a result, there are major economic and policy interests in defining access to data on learning. Regulatory approaches that focus on data privacy only partially address the emerging challenges and opportunities in this area.

Re-use and secondary uses of data generated on digital learning platforms will, therefore, be an important topic for policymakers in the coming years. In Europe, there have been various efforts to ensure data sharing, in particular the Data Act and the Data Governance Act, both aimed at establishing a single market for data. To achieve this vision, the focus cannot solely be on technical aspects, because other factors such as trustworthiness and effective data governance are also crucial (Farell, E., et al, 2023).

From a technical point of view, enabling and regulating access to learning data requires the definition of information architectures that address such concerns. Current learning analytics specifications, such as xAPI<sup>36</sup> and Caliper Analytics,<sup>37</sup> define some basic

data structures that can be used to record learner activity on learning platforms. These architectures, however, need to be complemented by knowledge about learning, so that data that are collected will be useful and relevant for learning and education.

Data spaces for learning and education, therefore, are conceptually different from European data spaces that are currently being developed for skills data.<sup>38</sup> Learning data consist to a large extent of trace data that records learning processes instead of outcomes. Although the EU Data Space for Skills (DS4Skills) project is at present developing conceptual approaches and some use cases for learning-related data, it will only address topics that are important for learning analytics, educational innovation, and the development of AI systems for education and learning in a limited way. As part of the broader European data governance and federation initiative Gaia-X, the public interest association Prometheus-X is in the process of bringing together actors in the educational sphere to develop a governance system for education and skills data. One of the use cases of Prometheus-X is for enabling actors to pool aggregated data in order to train artificial intelligence algorithms.<sup>39</sup> This work, however, is still in its early stages.

Learning is about personal development, and fine-grained data on learning processes are inherently personal. This means that existing regulations on personal data, data governance, and privacy are important factors in shaping the information architecture. More generally, what data are collected and how they are used needs to be justified based on socially accepted understanding about the aims and objectives of education. This links the ethics of education to the in-

36. <https://www.adlnet.gov/projects/xapi/#resources>

37. <https://www.imsglobal.org/spec/caliper/v1p2>

38. <https://www.digitaleurope.org/data-space-for-skills/>

39. <https://prometheus-x.org/>



formation architectures that support education. Data structures, in this sense, are inherently political and those structures used for education will require specific attention on how they should be regulated and what kind of data can be collected. Efforts aimed at empowering individuals to gain ownership on their data are particularly relevant in this regard. Solid has already developed a specification enabling people to store their data securely in decentralized data stores<sup>40</sup> and there are examples of prominent initiatives within the EU, such as the Flemish Data Utility Company.<sup>41</sup>

New federated computational and data architectures (Kaissis et al., 2020) can preserve personal data in large-scale machine learning and data-analytics, and they could become important for educational data infrastructures. They could, for example, address many of the requirements of GDPR. The concepts of personal data and privacy, however, are complex (e.g., Etzioni, 1999; Roessler & Mokrosinska, 2015; Sax, 2018). To better understand what privacy means in practical educational contexts, we would need to elaborate and study a variety of use cases. For instance, existing uses of AI such as online proctoring (Coghlan et al., 2021; Henry & Oliver, 2021; Mutimukwe et al., 2023) would benefit from EU level policies.

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40. <https://solidproject.org>

41. <https://www.vlaanderen.be/digitaal-vlaanderen/athumi-het-vlaams-datanutsbedrijf/the-flemish-data-utility-company>

# 4 AI and learning analytics

Digital learning has dramatically increased the amount of data that can be used to analyse learning processes and outcomes. As a result, interest in fields such as Learning Analytics (LA) and Educational Data Mining (EDM) has grown rapidly during the last decade.

‘Learning Analytics’ commonly refers to the measurement, collection, analysis and reporting of data about learners and their contexts, for purposes of understanding and optimizing learning and the environments in which it occurs (Lang et al., 2017). ‘Educational Data Mining’, in turn, focuses on the development of methods for exploring the unique types of data that come from an education context (Romero et al., 2010). There are many overlaps between LA and EDM (Siemens & Baker, 2012), and as machine learning is increasingly being used in both, these overlaps are growing. Educational institutions also generate data for many regulatory and management purposes, ranging from web usage statistics and telemetry data to scheduling, planning, and monitoring (Kitto et al., 2020), and open school data (OSD) policies are becoming commonly adopted around the world (Poisson, 2021). It is reasonable to assume that ‘in the future, administrative and real-time learning data will be updated and analyzed in real time’ (De Witte & Chénier, 2023).

In general, the amount of data collected on learning and education is growing fast. As noted above, this has also been characterized as the datafication of learning and learners (Lupton & Williamson, 2017). On

the other hand, data-driven AI requires data both for system development and operation, and the potential benefits of AI in education can only be realized with access to data on learning, not only by engineers and data developers but also by educational stakeholders.

Until recently, AI in education (AIED) has mainly relied on knowledge-based AI instead of machine learning approaches (Holmes & Tuomi, 2022). Whereas data-driven AI uses often large amounts of data and machine learning to come up with predictive models, knowledge-based AI requires explicit representation of knowledge structures. This usually means that human experts need to describe and define domain knowledge, for example, in terms of rules, expectations, or semantic relations.

This history of AIED is very rich both in pedagogical ideas and computational approaches. Much AIED research has focused on intelligent tutoring systems (ITS), where personalised learning has been supported by individualized sequencing and spacing of content to be mastered (Tuomi, 2023a). Although prototypical ‘screen-level’ intelligent tutoring systems have been extended to ‘classroom-level’ AIED and beyond, and many alternative pedagogic approaches have been studied also in the context of intelligent tutoring systems (du Boulay, 2019), rapid advances in data-driven AI over the last decade have now introduced AI in educational settings in unexpected ways too. In particular, the recent easy access to generative AI tools has highlighted the



potential of AI in education for the general public, while prompting concerns about the use of student data to improve its function

The state-of-the-art in AI is advancing very fast. Whereas AI systems have until now been limited to well-defined and specialized tasks, large language models, such as OpenAI's GPT-4, now seem to be able to emulate some human performance in relation to a diverse range of intellectual tasks. Whether such achievements can actually be counted as general AI remains a hotly debated topic in the field (Bubeck et al., 2023; Knight et al., 2023). There is, however, a general agreement that AI will have a transformative impact on education and learning in the coming years.

Policy efforts, most notably the EU Artificial Intelligence Act (European Parliament, 2023), will play a key role in both harnessing the opportunities and mitigating the risks of AI, particularly in education, signalling some use cases that could be considered as 'high-risk' and highlighting the need for AI Literacy.

## 4.1 Generative AI for teaching and learning

AI can be used in learning, for learning, for teaching, and for education administration (Holmes et al., 2019). Fast improvements in data-driven large language models have led some observers to believe that AI-supported personalised learning is now becoming possible, and education, in fact, will soon become a major driver in commercializing consumer AI (Skates, 2023).

Applications such as language translation, search, speech-to-text, and text-to-speech, rely on data-driven AI, and they are frequently utilized by both students and teachers. In recent discussion most attention has been paid to generative AI foundation mod-

els that can be adapted to various tasks. These models include, for example, the large language models that underpin generative AI systems such as Google's BERT (Devlin et al., 2018), OpenAI's GPT-3 (Brown et al., 2020), and the BLOOM open-source language model (Scao et al., 2022). Dialog-based modifications of these systems, such as OpenAI's ChatGPT, Microsoft's GPT-4 derivative Bing Chat, Google's Bard, and Meta's LLaMa have become widely popular with speeds that greatly exceed earlier technologies.

There are now many general-purpose AI models available for experimentation and commercial use.<sup>42</sup> The development of state-of-the-art data-driven AI systems, however, often requires internet-scale data and extraordinary amounts of computing power. This has resulted in dynamics that will link not only innovation and education, but also environmental policies in novel ways.

### 4.1.1 The emerging AI ecosystem

At present, it is not clear what the emerging AI ecosystem will look like in the medium-term or even near future. It is possible that it will be dominated by a small number of very large firms that have been characterized as 'google-sized natural monopolies of the Internet' (Tuomi, 2020). It is also possible that the recent fast progress in AI will hit technical barriers that allow many small players to catch up with the leading AI developers. For example, state of the art data-driven AI systems require very large amounts of energy, potentially making AI an important driver of global warming (Bender et al., 2021; Luccioni et al., 2022; Masanet et al., 2020; Strubell et al., 2019; Tuomi,

42. In April 2023, the machine learning platform Hugging Face Hub (<https://huggingface.co>) provided access to over 187,000 models and 31,000 datasets.

2020). More recently, the water usage of data centres has also become a problem (Siddik et al., 2021). AI researchers, governments, and others have called for tighter regulation and a total moratorium on AI development (Klein, 2023).

Unless the AI industry hits roadblocks, existing models of industrial innovation suggest that the large variety of AI system designs that follow recent technological breakthroughs will become consolidated in a small number of ‘dominant designs’ (Utterback, 1994; Utterback & Abernathy, 1976). One could argue that this has already happened with generative AI models as they are typically based on the same ‘transformer’ architecture. According to the Abernathy-Utterback model of product and process innovation, the ‘fluid phase’ of innovation, where many different alternative designs are introduced and search for a market, is then superseded by a phase where process improvement dominates. If this is the case, it can be expected that a small number of organizations will control the future AI ecosystem.

During the last years, improvements in AI performance have been associated with larger models, more data, and higher processing requirements. This has made even the largest AI developers worried that they will run out of compute capacity soon (Tuomi, 2020). A recently published fundraising pitch deck of the OpenAI spin-off Anthropic stated that the company will need up to \$5 billion to become competitive in the generative AI market (Wiggers et al., 2023). More interestingly, Anthropic argued that the companies that are able to train the best models in 2025/6 will be so far ahead that no-one will be able to catch up with them in subsequent cycles. Anthropic expects that it would be able to develop ten times more powerful AI mod-

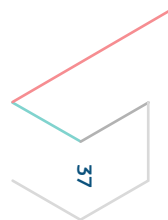
els than the current state-of-the-art using compute clusters that would contain tens of thousands of GPUs. OpenAI itself has become allied with Microsoft, which in early 2023 invested several billion dollars in OpenAI. Much of this cost is for compute capacity that is needed to train large language models.

Training foundation models requires compute power that only few organizations can afford. For example, the open-source BLOOM model was trained for 3.5 months on 384 A100-80GB enterprise level GPUs (Scao et al., 2022). The current price for these processors is above €15,000 each. Application-specific fine-tuning of existing foundation models can be done with less compute, but as the models are very large (e.g., 176 billion parameters in BLOOM), only large AI developers have the required infrastructure for this. BLOOM was therefore created by a large group of AI researchers with the aim to democratize access to large language models.

What such a democratization means in practice is an important question which also has implications for education policy.<sup>43</sup> From the point of view of innovation dynamics, an open-source large language model such as the BLOOM provides equal access to a ‘foundation model’ for many innovators. This model can then be used to develop a large variety of applications. At the same time, it becomes a shared platform and a technological artefact where the interests of many developers and users meet. The resulting inter-dependencies mean that in-

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43. Beyond computing capability, the training of large language models also requires extremely large amounts of data. This is a challenge for smaller languages and domain-specific applications. For example, the TurkuNLP research team at the University of Turku has released an open-source language model for the Finnish language. This is a 13 billion parameter model developed using the LUMI supercomputer, which is the fastest supercomputer in Europe. The researchers note that they are now starting to run out of Finnish language resources (Jakobsson, 2023).



novation in the foundation itself needs to slow down and become controlled.

A similar innovation dynamic made possible the historical development of the Linux open-source ecosystem (Tuomi, 2002). The tight control of the Linux core operating system, or its 'kernel', enabled very fast expansion of Linux and the related applications. Under such innovation dynamic, it can be expected that a small number of domain-specific large language models will emerge in the near future. An early example of such a domain-specific model is the BloombergGPT, developed for the financial sector (Wu et al., 2023).

If Anthropic is right, and massive investments guarantee sustainable dominance in the emerging AI ecosystem, or if open-source foundation models such as BLOOM can avoid the emergence of natural monopolies and oligopolies, both alternatives will have important implications for education policy. National policymakers have traditionally formulated educational policies that address local needs. EU Member States are responsible for the configuration of their respective education systems, while the Union plays a supporting role by means of actions designed to improve the quality and efficiency of education and training, as well as to promote lifelong learning and mobility.<sup>44</sup> As a public service, education is part of the remit of national, regional or local governments in EU Member States. However, the increasingly central role of technology in education is resulting in a growing reliance on global actors. The wide use of digital platforms also means that large global platform providers probably now have access to more data about students and education providers than teachers, educational institutions, or policymakers. The extraordi-

nary dynamics of data-driven AI therefore generates an industrial and innovation ecosystem whose structure has direct impact on education.

The economic cost of developing state-of-the-art foundation models is high for small start-ups, but small when compared with the costs of education. It is commonly estimated that the cost of training of OpenAI's GPT-3.5 (on which ChatGPT was based when it was originally released) was between \$2 and \$5 million. The training cost for Google's PaLM has been estimated to be \$8 million (Maslej et al., 2023, p. 62). Such estimates typically include only the compute costs for training the model. These probably represent only a fraction of the total costs that include the iterative development and training of several related models, data collection and curation, and other similar costs. The total cost still remains a fraction of the total cost of education. Accordingly, we may consider whether part of the costs could be shifted to governments if educational benefits are identified from developing foundation models (or, for example, training such models for small regional European languages).

Machine learning architectures for large language models are, however, also becoming more efficient, and there are several ways in which high-performance models can be made smaller. For example, DeepMind's Chinchilla (Rae et al., 2022) performs on par with the earlier 280 billion parameter Gopher with one fourth of the parameters. Similarly, with some additional training using human feedback, OpenAI's InstructGPT was able to generate outputs that the users preferred over the responses of GPT-3 that had 100 times as many parameters (Ouyang et al., 2022). However, the bene-

44. Treaty of the Functioning of the European Union, Article 6.

fits of even larger models are actively being studied, and the development of increasingly large models continues. For example, in April 2023 Google switched its Bard from the 137 billion parameter LaMDA model to its 540 billion parameter PaLM model.<sup>45</sup> The latter was trained using 8192 Google's TPU AI processors on a platform that can theoretically achieve up to 1.1 exaflops, or 1.1 million trillion calculations per second.

The different variants of Meta's recently published instruction-following LLaMA use a much smaller number of parameters (7B, 13B, or 65B) than PaLM or the 175 billion parameter GPT-3. LLaMA is an open-source large language model released in February 2023 that can be fine-tuned for user applications. Due to its relatively small size, this is also possible with limited computational resources. For example, researchers at Stanford University did this with their Alpaca model, fine-tuning it with just a few hundred dollars of rented computing capacity. Researchers from UC Berkeley, CMU, Stanford, and UC San Diego further improved on Alpaca, training their Vicuna model using 70,000 user-shared conversations.<sup>46</sup> Using OpenAI's GPT-4 to compare the quality of the conversation outputs, Vicuna was estimated to achieve about 90 per cent of the ChatGPT performance. From the point of view of practical applications this is remarkable as the cost of training of the 16 billion parameter LLaMa-based Vicuna was

about \$300.<sup>47</sup> Recent research (Gudibande et al., 2023) has, however, also suggested that these cheap derivatives of large language models have important limitations that can be overcome only by developing larger models.

Although dialog-based text-to-text models, such as ChatGPT, have attracted much attention among educators, generative AI systems have also been developed for many other areas. OpenAI's Codex, which is also based on the GPT-3 architecture, has been widely used for computer programming. Amazon launched its CodeWhisperer, 'a real-time coding companion' based on a large language model, in April 2023. Related text-to-image generators such as OpenAI's DALL-E 2, Stability AI's Stable Diffusion, and Midjourney have become important tools for graphics design and image production.

OpenAI's GPT-4 broke new ground in generative AI as it can use both text and image inputs. Multimodal large language models that can see and talk are rapidly becoming available. An example is the multimodal large language model KOSMOS-1, developed by Microsoft researchers, which encodes images as a form of language and uses a large language model to reason about the image content (Huang et al., 2023).

Low-cost access to large foundation models developed by the leading AI developers has led to very rapid growth in data-driven

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45. The exact model sizes used for Bard have not been published, but it is known that Bard was built using LaMDA. The CEO of Google has characterized the original Bard as a 'Honda Civic' among race cars (Roose et al., 2023), which suggests that one of the smaller LaMDA models could have been used for the first Bard version.

46. <https://github.com/lm-sys/FastChat>

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47. It should be noted that Alpaca and Vicuna are both fine-tuned versions of Meta's LLaMa, and the costs of pre-training the LLaMa model are not included in these estimates. The training costs for GPT-4 are not publicly known, but OpenAI's research papers suggest that GPT-4 was trained with 1000 times more computations than GPT-3.5. The number of parameters in GPT-4, however, could be similar to GPT-3.5 as presumably much more data were used to train GPT-4. ChatGPT has been claimed to have 20 billion parameters, but it is often also said to have 175 billion parameters, probably because this number is known for GPT-3.5. At present, the most recent version of ChatGPT (ChatGPT Plus) is based on GPT-4, but OpenAI has not published technical details of the system or its training.

AI products aimed for learning and teaching. The dominant industrial actors are trying to establish commercial platforms that would become central points in the emerging ecosystem. For example, in April 2023 Amazon launched its Bedrock service that provides access to several state-of-the-art foundation models.<sup>48</sup> These can be linked with other Amazon services for large-scale cloud-based deployment.

Beyond the established knowledge-based AIED tools, many start-ups now use data-driven AI technologies. These cover the full range from early childhood to primary, secondary, tertiary, and lifelong learning. As the early excitement about the capabilities of generative AI recedes, and the limitations of large language models become better known, generative AI systems will increasingly be combined with knowledge-based AI. Examples of such ‘augmented language models’ are discussed below, but knowledge-based AIED research will have more visible influence in the development of AIED systems in the future. For example, when Khan Academy announced its GPT-4 powered Khanmigo in March 2023, it noted that Khanmigo was informed by instructional models developed for the well-known knowledge-based AutoTutor (Nye et al., 2014).

For pedagogic uses, generative AI applications – such as video captioning, translation, video summarizing and highlight extraction, text-to-animation, and voice to synthetic video – provide many new opportunities. These can be used, for example, in generating new learning materials from existing content. For example, voice samples can be used to clone a human speaker, and the produced synthetic voice can be used to transform text to speech, which can then be used to animate still images or animated

characters.<sup>49</sup> This would allow, for example, a teacher to automatically generate video lectures in multiple languages using lecture notes written in the teacher’s native language.

Although the initial reaction to the publication of the ChatGPT at the end of 2022 was largely focused on potential misuses of emerging technologies and ‘cheating with AI’, at present the focus is shifting to the ways in which generative AI could support learning and teaching (Sabzalieva & Valentini, 2023; U.S. Department of Education, 2023). In many of the proposed educational applications, ChatGPT collaborates with the learner, for example, as a Socratic opponent, co-designer, motivator, or study companion.

ChatGPT and other generative AI systems can clearly be used in education in many ways. Personalised tutoring systems can now be developed in days using ChatGPT prompts, and, in addition to Khanmigo, this approach has already been used in some ChatGPT plugins. On a more systemic level, critical discussions on the potentially conflicting interests of commercial stakeholders and educators, as well as the need to understand the various interests of the stakeholders continues (e.g., Blikstein et al., 2022; Selwyn, 2022b; Selwyn, 2023; Williamson, 2021; Williamson et al., 2022). In general, the AI ecosystem is evolving very fast and shaping both AIED research and the AIED industry. Policy developers would greatly benefit from a better understanding of this emerging AIED ecosystem and its implications for policy.

49. Low-cost voice cloning services and video generators are now widely available. For example, ElevenLabs (<https://beta.elevenlabs.io>) can clone voices and use these to translate text to speech. D-ID (<https://www.d-id.com>) markets its Creative Reality Studio, for example, as a tool for educators that can convert a photo with text or cloned audio into an interactive and engaging video presenter in over 100 languages.

48. <https://aws.amazon.com/bedrock/>



### 4.1.2 Abstraction and generalization in generative AI

A noteworthy aspect of these generative models is that their capabilities have regularly surprised their developers. For example, the DALL-E text-to-image generator apparently was able to make combinatorial generalizations (e.g., ‘a tapir made of accordion’) and variable binding (e.g., ‘a baby hedgehog in a Christmas sweater walking a dog’) (Ramesh et al., 2021). This is surprising as the underpinning language models are trained simply to predict the next word in a sequence of words, without any explicit models of ‘generalization’, ‘abstraction’, or ‘concept formation’. Some observers of the GPT-4 development went further, arguing that the system had gained unexpected high-level thinking skills that could properly be called ‘sparks of general intelligence’ (Bubeck et al., 2023). As abstraction, generalization, and concept formation are central topics for learning theories, they are also highly important for understanding the future possibilities and limitations of the use of data-driven AI in education and learning (Tuomi, 2018b). Although data-driven AI systems use purely behaviouristic learning processes and have been characterized as ‘artificial instincts’ and ‘stochastic parrots’ (Bender et al., 2021; Tuomi, 2018a), a better understanding of their emergent capabilities for abstraction and generalization will be highly important both for theories of learning and for AIED system design.

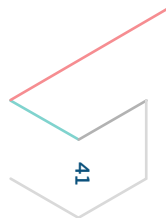
### 4.1.3 The future of writing

Writing is a key transversal competence, and in many theories of learning it has been viewed as a key for cognitive development. Writing skills are also important in many professions and occupations. It is, therefore, not surprising that generative AI systems that can produce high-quality text have been viewed as a threat to education

and, more generally, human cognition. In the words of one commentator from the Stanford Institute for Human-Centric AI, automated writing tools are ‘a disaster in making’ and potentially corroding our creative abilities. This is because ‘becoming a good writer is the same thing as becoming a good thinker’ (HAI, 2023, p. 20).

In the 1920s Vygotsky (1986) emphasized the fact that writing is an unnatural skill for a child. It is a tool that allows individuals to communicate and express their ideas and thoughts, and as such it requires direct social communication and interaction to be replaced by a mediated one. For a child who has learned that spoken words generate immediate reactions in its environment, it looks unnecessary to write words on paper. In contrast to orality, writing is artificial as Ong (1982) has also pointed out. While there are immediate benefits from writing for individuals – as the ability to record words effectively expands one’s own memory and consciousness – benefits to society at large emerge primarily at a cultural and historical level, where writing makes inter-generational communication possible. Such communication can further be accumulated in conceptual and theoretical systems.

For Vygotsky, advanced forms of thinking develop in a child when communicative speech becomes an internal tool for linguistic thinking. Culturally developed conceptual systems enable increasingly abstract forms of thought, and the child learns these conceptual systems through instruction and education. From such a Vygotskian point of view, generative AI systems are not interesting because they produce text; instead, their relevance for education is in their capability to engage humans in advanced forms of thought where concepts, conceptual systems, and language are the tools for thought. In such a developmental context, it



is not informative to ask whether paper or pencil corrodes our creative abilities. More interestingly, we can ask how pen, paper, books, archives, typewriters, or AI become integrated in thought. Similarly, we can ask how generative AI can become part of human cognitive processes. As with other previous technologies, it is likely to disrupt writing, but it is also likely to transform the way we think or utilize writing for learning.

In general education, large language models show great promise in text analysis and writing support. Text summarizing, outlining, and formative writing support have been important topics in knowledge-based AIED for a long time (e.g., Knight et al., 2020; Strobl et al., 2019). Large language models are now increasingly used to generate summaries of textbook chapters and, for example, academic articles. The same text can be summarized for different user groups based on their age, language capabilities, or preferences. Data-driven AI can also analyse written text from various points of view, helping the author to reflect upon the produced text.

Commercial products in this area include, for example, Rephrasely,<sup>50</sup> which converts user sentences from one style to another in over 100 languages, and Jasper<sup>51</sup> that generates text for blogs, websites, social media, and – as suggested by the developers of Jasper – also love letters, based on user prompts. Large language models are also currently integrated in collaboration and knowledge management tools. For example, the collaboration and note-taking platform Notion<sup>52</sup> now supports the generation of summaries and insights of user notes, document rewriting, translation, and tone change, as well as the creation of doc-

ument drafts. Researchers have also explored more broadly the nature of AI-supported creativity and writing (e.g., Sharples & Pérez y Pérez, 2022), and suggested that AI provides opportunities to experiment with novel pedagogic models.

As generative AI becomes integrated in various text- and language-related tasks, we may need to rethink the nature of writing. For example, Buckingham Shum (2023) has proposed that generative AI could transform writing in ways that resemble the changes in music production during the last decades. Since the early 1990s, professional-quality music production has become widely accessible as digital audio workstations have replaced expensive recording studios. Programmable music synthesizers and audio effects can now easily be combined with sampled voices and recorded audio and arranged into final products using specialized music production interfaces, non-linear editing tools, and AI-supported audio processing. Buckingham Shum's 'writing synth hypothesis' proposes that with the emergence of generative AI, authors will be able to learn writing in new ways, democratizing writing just as we saw with music synthesizers.

A special form of text production, often claimed to be important in the emerging digital world, is computer programming. Although fully automated program generation is still a challenge, several systems have recently been used to support both professional software development and more novice programmers. Github Copilot, powered by OpenAI's Codex, is now widely used to improve programmer productivity. Amazon's CodeWhisperer can generate program code from simple natural language prompts. Somewhat surprisingly, the generic ChatGPT has also shown remarkable capabilities in generating program code from

50. <https://rephrasely.com/>

51. <https://www.jasper.ai/>

52. <https://www.notion.so/>

natural language prompts and in analysing and explaining the functionality of existing code fragments in natural language.<sup>53</sup> Recent code-generation systems, such as DeepMind's AlphaCode (Li et al., 2022), suggest that AI-based code generation can already outperform highly skilled human programmers in some cases. These developments have implications for the demand of advanced digital skills and related policies, for example.

#### 4.1.4 Prompt engineering and in-context learning

Generative text-to-text AI systems are developed by iteratively pre-training the AI model, often with thousands of trillions of computations and hundreds of billions of words. This process creates 'baseline models' such as the GPT-3. The baseline models can then further be retrained or fine-tuned for specific tasks, for example so that they become better at providing relevant outputs (e.g., in legal or medical domains), or in responding to textual instructions. An important example of such a fine-tuned model is the InstructGPT (Ouyang et al., 2022), which has further been refined into the well-known dialog-based ChatGPT.

Large language models are trained to predict the following word given a list of preceding words. A technical breakthrough in this area was the 'transformer' architecture that effectively uses a broader textual context for this prediction than earlier models (Vaswani et al., 2017). When transformer models are used to generate text, they use a given 'prompt text' and extend this initial context with the generated word sequence to predict the next word. In the original ChatGPT model, this context had approxi-

mately 3000 words. This means that the output will greatly depend on the prompt, and the system can be 'steered' by modifying the prompt. In contrast to pre-training, this is called 'in-context learning' (Brown et al., 2020). Parts of the prompt, a 'system prompt', can be defined by the system developer to guide the system output towards predefined tasks. The remaining part, a 'user prompt', is typically given by the end user. The generated output strongly depends on the prompt, and for example, the order of sentences and words in the prompt (Gao et al., 2021; Wei et al., 2023; Zhao et al., 2021). The skilful design of prompt texts, or 'prompt engineering', has therefore quickly become important for effective use and deployment of generative AI systems.

Large language models can, therefore, be trained on three very different levels. The textual training data provided to the base model defines its behaviour, which can further be refined by fine-tuning with task-specific data. The behaviour of the model can, however, also be changed by prompts. Large language models can, therefore, be 'programmed' through natural language prompts and telling the model what it is expected to do. These instructions can provide a few examples of the sought-after behaviour, or just a single instruction without further guidance. The former is known as 'few-shot learning', and the latter as 'zero-shot learning'. Zero-shot learning can also be used to prompt an image generating model that translates a textual description into an image, animation, or video (Ramesh et al., 2021). In-context training can be done in real time, and allows the system to adapt to information that was not available when the base model was trained. In-context training also often leads to better performance than traditional model fine-tuning (Caron et al., 2021).

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53. Because of the increasing capabilities of generic large language models, OpenAI has now discontinued support for the Codex API.

ChatGPT became an instant success after its release because large language models are surprisingly good few-shot learners. When some generic instructions are defined by the system developers – for example on what a dialogue should look like – the end users see a zero-shot learner that can meaningfully answer questions and generate text based on a single instruction.<sup>54</sup> In ChatGPT, the system is fine-tuned using examples on how to respond to instructions, and its behaviour is further guided by in-context learning.

The importance of effective domain-specific prompt design has quickly been noted, and there is now a rapidly increasing group of people claiming to be specialists in this area. At present, good prompt design is very much an art form that requires a good understanding of the behaviour of the base model. Automated methods for refining optimal prompts are currently being developed (e.g., Zhang et al., 2022; Zhao et al., 2021), but most prompt design occurs at present manually on top of vendor-tailored end-user applications, such as ChatGPT, Codex, and Stable Diffusion. There are also open-source initiatives, such as the LangChain Hub,<sup>55</sup> that aim to develop and share predefined prompts for various use cases.

As the underlying language models are continuously changing, it is not clear that deep expertise can emerge on prompt engineering on these platforms. There are, however, some general guidelines for effective prompt design. For example, using prompts that clearly define expectations and push the language model to elaborate its reasoning can substantially improve system performance (Kojima et al. 2023). However,

it is clear that standardized evaluation metrics will be important for the measurement of quality and effectiveness of domain-specific prompts that orient the language model, for example, in educational applications. The evaluation framework that OpenAI published<sup>56</sup> together with GPT-4 is therefore potentially an important element in shaping the generative AI ecosystem. For example, it would be possible to develop evaluation benchmarks that measure how well a given generative AI system is aligned with the EC guidelines for the ethical use of AI in education and learning (European Commission, 2022a).<sup>57</sup>

Knowledge-based intelligent tutoring systems typically had sophisticated models of user's current knowledge. The development of algorithms for managing the user's knowledge model and the development of domain knowledge models has been a very labour-intensive task in traditional AIED. Large language models, in contrast, rely on user prompts to generate a temporary snapshot of user intentions and knowledge state. Agent-based language model architectures that have access to external memory, such as AutoGPT, BabyAGI, and other agents supported by LangChain,<sup>58</sup> can combine persistent and evolving learner models and generic domain models that can be refined for specific domains with minimal development effort. The possibility for lightweight personalization using well-designed prompts and user interaction could become important for just-in-time learning and training, for example. An important example of such an approach to personalization is the Khanmigo system, currently being piloted by Khan Academy.<sup>59</sup>

54. In this architecture, the developer-provided prompts can sometimes be deleted, overwritten, or by-passed, with the result that the system can operate as the fine-tuned base-model, without further restrictions defined by the developer. This form of system cracking is called 'jail-breaking' and the resulting systems are called DANs (Do Anything Now).

55. <https://github.com/hwchase17/langchain-hub>

56. <https://github.com/openai/evals>

57. The EC ethical guidelines are based on a capability-based approach, and it is possible to test generative AI systems using the defined ethical capabilities. These are operationalised in the EC guidelines as rubrics.

58. <https://blog.langchain.dev/agents-round/>

59. <https://www.khanacademy.org/khan-labs>

### 4.1.5 Trustworthiness and alignment in generative AI

Pure language models such as ChatGPT are notorious for their ability to generate convincing text that is factually wrong. Large language models have also traditionally lacked mathematical skills (though this has recently improved), are unable to access up-to-date information on recent events, are unaware of the progression of time, have difficulties in understanding languages that are not widely used on the internet, and invent facts and hallucinate non-existing realities.<sup>60</sup>

To reduce factual errors and ethically and politically unacceptable output text, ChatGPT uses a human-assisted learning process (reinforcement learning from human feedback, or RLHF) (Glaese et al., 2022; Stiennon et al., 2022). For the time being it is not clear whether this approach can be effectively scaled up. It is, however, possible to improve the trustworthiness of large language models by linking them to existing knowledge sources. This approach will also be important for education and learning.

A disruptive recent development in generative AI has been the introduction of plug-in and agent-based approaches. Agents use language models to reason about the next steps that are needed to perform a given task. An example is the Toolformer architecture (Schick et al., 2023). Toolformer is a language model based on a small GPT transformer model (GPT-J), but it has been additionally trained to predict external data sources and tools that can be used to get accurate information. A range of tools, such

60. For example, in 'closed-domain' tasks, such as summarization and closed-domain question-answering, where the output should not contain information that is not present in the input, GPT-3 had a 41% hallucination rate (Ouyang et al., 2022, p. 3). In GPT-4 and ChatGPT, hallucinations are reduced by training a separate model that rewards factually correct responses.

as a calculator, a question-answer system, a search engine, a translation system, and a calendar have been integrated in the Toolformer architecture. A similar approach is used in WebChatGPT<sup>61</sup> that adds a web search plugin to the browser that can augment the user's prompt with data found from the web. These functionally extended AI models are also called 'augmented language models' (Mialon et al., 2023).

Augmented large language models gained visibility when OpenAI started to roll out ChatGPT plugins at the end of March 2023.<sup>62</sup> An interesting open-source variant of this approach is the LangChain framework,<sup>63</sup> which supports the chaining of language models, actions, and agents. This makes it possible, for example, to augment the language model dynamically with data from the internet, from local databases, or from previous interactions with the system. In education, one possibility would be to link language models with knowledge-based models generated from textbooks and existing assessment rubrics.<sup>64</sup>

The general challenge of filtering ethically, or otherwise unacceptable outputs, in generative AI is known as the 'alignment problem'. This challenge is commonly addressed by fine-tuning the base model to reduce harmful outputs and to increase the probability of useful outputs. Recent research has also tried to address this problem by using machine learning instead of human intervention. An example is Anthropic's Claude language model (Bai, Kadavath, et

61. <https://github.com/qunash/chatgpt-advanced>

62. <https://openai.com/blog/chatgpt-plugins>

63. <https://langchain.com/>

64. It is useful to note that large language models erode the traditional distinction between knowledge-based and data-driven AI. Whereas in the knowledge-based approach domain models were handcrafted by expert 'knowledge-engineers', large language models have internal domain models that emerge in the training process. Because of this, large language models can be used as 'expert' reasoners in the agentic approach discussed above.

al., 2022). Claude specifically aims to be a ‘constitutional AI model’ whose outputs are automatically trained to reduce their potential ‘harmfulness’ based on externally defined ‘constitutional principles’. This approach is similar to the RLHF, which is used among other things to fine-tune OpenAI’s ChatGPT, though Anthropic relies on AI-automated reinforcement learning (RLAIF).

The idea that explicitly defined constitutional principles and moral maxims could form an ethically justified foundation for societies has a long history in political sciences, legal theory, and ethics.<sup>65</sup> The developers of Claude have adopted a rather straightforward interpretation of such principles. At present, the ‘constitution’ of Claude consists of 16 ‘principles’ that the language model uses to learn to rewrite its responses in less harmful ways. The ‘harms’, themselves, are classified using nine categories, including ‘discrimination and injustice’, ‘general unethical behaviour’, ‘bullying or harassment’, and ‘misinformation or conspiracy theories’. The interpretation of such principles, of course, is problematic from ethical and cultural points of view. It has been argued, for example, that the ethics of AI cannot be based on universal principles (Mittelstadt, 2019), that a more socio-developmental approach is particularly needed in the educational domain (Tuomi, 2023b), and that in general ethical principles depend on cognitive metaphors that have many incompatible interpretations (Lakoff, 1996). Alignment of generative AI in the educational domain would therefore imply alignment with some explicit articulation of ethics of education.

In general, ‘alignment’ at present is about ‘alignment with developer and evaluator

preferences’. Any technical definition of alignment will eventually need to be based on specific ethical and political theories that state how preferences or values are expressed in the social domain, and how they are taken into account in collective action and social choice. As various alignment methods are now being developed to make AI more ethical, trustworthy, and acceptable for various user groups, including school-age children, it would be important to gain better understanding of the appropriate principles in educational settings, as well as the limits of such alignment approaches. In general, alignment research is now viewed as a central technical and theoretical challenge in generative AI research (e.g., Gabriel, 2020; Kenton et al., 2021; Weidinger et al., 2021). It is, however, clear that our understanding in this socially and politically important area is still quite elementary.

## 4.2 Open learner models, agency, and humans-in-the-loop

Knowledge-based intelligent tutoring systems require ‘learner models’ that represent the learner’s knowledge state. In many influential AIED systems, user models have been updated based on monitoring user’s performance while the student progresses through the learning tasks. Such learner models are updated by the system, and the system uses information in the learner model to steer system behaviour. In traditional intelligent tutoring systems (ITS) the learner model serves the needs of the system but remains opaque for the learner.

To support reflection and self-regulation in learning processes, AIED researchers have since the 1990s experimented with various types of ‘open learner models’ (Bull et al., 1995; Bull & Kay, 2010; Brusilovsky, 2023; Bull, 2020). Open learner models, in effect,

65. For example, in his *Law of Peoples*, Rawls (1999) proposed an ideal social contract theory, or a ‘universal constitution’, that could and should be accepted by both liberal and non-liberal societies.

open up the black box of the learner model in traditional knowledge-based ITS, and allow the learner to understand how learning proceeds. In contrast to content-oriented views on instruction and education, research on metacognition and cognitive development highlight learning as a process that enhances our capacity for thinking. Important aspects of this capacity are self-regulation (Azevedo et al., 2019) and socially shared regulation (Järvelä et al., 2023) during learning processes. Mastery of the content to be learned plays an important role, but only an auxiliary one (Tuomi, 2023a).

Metacognition and reflection play a central role in many influential theories of learning (e.g., Dewey, 1991; Piaget, 1971; Schön, 1987; Vygotsky, 1986). Vygotsky (1986, p. 166), for example, held that those higher intellectual functions that are at the fore of development during the early school age are characterized by reflective awareness and deliberate control. Similarly, Piaget emphasized the all-important role of self-regulation (e.g., Piaget & Inhelder, 1979, p. 159). Learning, for Dewey, Vygotsky, and Piaget, is about the development of intelligence and the capacity to control it. The increasing capabilities for self-reflection, equilibration, and self-regulation are the signposts in this process.

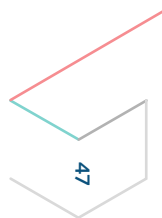
Such a developmental view on education becomes important when AI and learning analytics systems are used to support learning processes. As domain-specific knowledge becomes easily available and its lifetime is often short, the focus on education shifts from content transfer towards meta-cognition, including learning strategies. Open learner models can then be used, for example, to represent the learner's knowledge to the learner, allowing them to reflect on their learning. Beyond helping to focus on content areas where attention is needed, AI can be used to generate mean-

ingful interpretations of the learning experience that help the learner to understand learning. Beyond automating instruction, AI can be used to develop capabilities for learning.

In such a developmental view on learning, AI systems become 'intellectual companions', 'learning partners', and 'cognitive tools' that support the development of thought. Over the decades, this view has been an important thread in the research on computer supported learning (e.g., Pea, 1985; Salomon et al., 1991; Salomon, 1993) and human computer interaction (Kaptelinin & Nardi, 2006), but it is again becoming prominent because generative AI systems can be used in this mode in many practical educational settings. This has implications, for example, for the ways in which agency is distributed in learning processes where humans and AI tools interact. When accumulated learning is used for work tasks performed jointly with such intellectual companions, the traditional concept of 'skill' also needs to be reconsidered.

#### 4.2.1 Distributed agency in education

The integration of AI systems with human learning processes makes agency a central concept in education. Agency has been defined in various ways in the research literature, and it has also gained increasing visibility in AIED and learning analytics research (e.g., Brod et al., 2023; Buckingham Shum et al., 2022; Jääskelä et al., 2021). Agency has often been understood in a decision-making context, for example, as the freedom and control in determining action (Sawyer et al., 2017). In many influential intelligent tutoring systems, the student simply had to perform actions determined by the machine. Editable open learner models that allow the student to interact with the system give the user some power over



the machine and allocate the student some agency. More broadly, in emerging AI-enabled learning systems, agency can be dynamically allocated among the computational system and the human.<sup>66</sup>

Strictly speaking, this distribution of agency is nothing new. It is a key characteristic in formal education, where teachers guide students on their learning path. In educational settings, the teacher is in the learning loop, and this is called instruction. A central idea in Vygotskian learning theories was that children learn with the help of more competent adults. Learning occurs in the ‘zone of proximal development’ where the child can use advanced form of thinking, but only when guided by someone who already has this capability, and who can provide cognitive scaffolding for the developing child (e.g., Rogoff, 1990; Wertsch, 1985). In the context of such theories, one can ask how hybrid AI-human systems can be integrated in the learning process (Järvelä et al., 2023; Luckin & Boulay, 2016; Molenaar, 2022; Scardamalia & Bereiter, 1991). One can also ask how AI could support new forms of agentic distribution in educational settings, for example, by putting the student, teacher, and the parent in the learning loop with AI. This requires that the common individualistic views on agency and competence are expanded to include those social and technical resources that underpin agentic action (Tuomi, 2022).

Learning analytics and open learner models can be used to support student self-reflection and self-regulation. When more agentic AI systems are used for this, dynamic division of intellectual labour becomes pos-

66. It is perhaps useful to note that one main claim in actor-network theory (Law & Hassard, 1999) was that there is symmetry between technical and human actors. In contrast, in activity theory (Kaptelinin & Nardi, 2006), technology does not have its own motives and the symmetry between humans and functional artifacts breaks down. It is an interesting question how these theoretical approaches should be revised when AI systems and humans share agency (Newman et al., 2019).

sible. In contrast to learning theories rooted in child psychology, research on knowledge creation has focused on adult learners and their social collaboration. In this context, learning has often been understood as the production of new knowledge.<sup>67</sup> The development of AI suggests that these studies could be reinterpreted in the emerging technological contexts. In contrast to the relatively static environments in a classroom, workplace environments vary with the tasks performed and tools used, and knowledge creation often becomes more important than assimilation of prescribed knowledge (Buckingham Shum et al., 2022).

Large language models are especially interesting in the Vygotskian theoretical context. For Vygotsky, language provides the foundation that makes the transition to advanced forms of adult thinking possible. For Piaget, a similar qualitative developmental transition resulted when a child internalized egocentric speech. According to Vygotsky, external tools and symbol systems that support human cognition are necessary for the development of a child. In educational contexts, the importance of large language models may, therefore, be less in their autonomous capacity to show ‘sparks of general intelligence’ than in their capability to transform human intelligence.

#### 4.2.2 Agency as capability

In a broader developmental and capability-based context, agency can be interpreted

67. The term ‘knowledge creation’ was introduced to the English-speaking organizational learning and innovation literature by Nonaka (1991, 1994). The term suggests that knowledge is socially constructed, but it also invites making explicit the epistemological assumptions that underpin models of learning. Nonaka’s work was informed by the phenomenological epistemology developed in the Kyoto school of philosophy, but other conceptual frameworks – such as autopoietic systems theory (von Krogh & Roos, 1995), anticipatory systems theory and category theory (Ehresmann et al., 2018), activity theory (Engeström, 1999), and semiotics (Paavola & Hakkarainen, 2005) – have also been used. A more static view on knowledge underpins management literature on organizational learning (e.g., Argyris & Schön, 1978; Hedberg, 1981; Levitt & March, 1988).



as the capability for informed and heedful action. Informed action requires information and knowledge. In the ethics of AI this has often been understood as the requirement of system transparency and explainability. The core concepts of AI system governance: transparency, explainability, and ‘human-in-the-loop’, therefore, can be understood in terms of agency. This makes open learner models relevant for the practical implementation of risk-based AI governance models in education, and beyond it.

A key assumption in open learner models is that learning requires self-reflection and self-regulation. For learning to occur, the learner must be able to participate in the human-machine loop as an agent. For responsible action, the learner further must be able to adjust the allocation of agency and, if needed, control the technical system.

In contrast to most discussions on AI governance, learning theorists would point out that agency is a developmental outcome. Whether a human in the loop can act as an agent depends on a person’s competences and the possibilities to express these in given cultural and normative contexts. These, in turn, largely depend on accumulated learning. Whereas AI engineers often approach explainability and transparency from a technical point of view, as access to data, a capability-based approach suggests that agency development would be a more productive starting point. Knowledge about learning, in other words learning theories, becomes therefore highly relevant for apparently technical discussions about explainability, transparency, and the control and governance of high-risk AI systems.

A key difference between knowledge-based and data-driven AI systems is the potential openness of user, domain, and inference models. Knowledge-based AI systems implement explicitly defined models of rea-

soning and the domain of system’s expertise. Because these knowledge structures are explicitly defined during system design, it is possible to represent and trace the reasoning process for the user. In data-driven AI systems the reasoning process is inherently opaque as it depends on the current state of often billions of parameter values. Because of this, data-driven AI systems are often regarded as ‘black boxes’.

The distribution of agency between a human and an AI system requires that both are able to track the other’s reasoning. Surprisingly, this seems to be something that can be done with large language models. When large language models are used in an agentic mode, they can be prompted to describe the reasons why they make specific choices. This is called ‘chain of thought’ prompting (Wei et al., 2023). A chain of thought can be induced simply by telling the model to ‘think step-by-step’(Kojima et al., 2023) or by giving it examples that demonstrate a series of intermediate natural language reasoning steps that lead to a final output. A sufficiently large language model can then follow this example and make explicit the intermediate steps that it uses in problem solving. For instance, Table 1 illustrates how after a user (i.e., human) inputs a sequence containing a gap in it (i.e., the second answer is missing from the prompt), the AI assistant (i.e., GPT 3.5) can infer that what the user wants is for it to produce an explanation of the situation presented in the third statement within the prompt submitted by the user. Whereas there has been much debate about the impossibility of explaining the behaviour and choices made by data-driven AI systems, language models can do what humans do: if asked, they can explain what they are doing and why. Nevertheless, just like humans too, they might well hallucinate or provide factually wrong information when providing such further explanations.



An example of chain of thought with GPT-3.5 is shown in Table 1.

Table 1: Chain of thought prompt with explanation

User	<p><i>Q: A coin is heads up. Daniel flips the coin. Romina flips the coin. Is the coin still heads up?</i></p> <p><i>A: The coin was flipped by Daniel and Romina. So the coin was flipped 2 times, which is an even number. The coin started heads up, so after an even number of flips, it will still be heads up. So the answer is yes.</i></p> <p><i>Q: A coin is heads up. Ilkka flips the coin once and then again.</i></p> <p><i>A:</i></p>
AI Assistant	<p><i>The coin was flipped twice, which is an even number. The coin started heads up, so after an even number of flips, it will still be heads up. So the answer is yes, the coin is still heads up.</i></p>

Source: the authors and GPT 3.5.

In the capability-based approach, agency characterises what a person is free to do and achieve in pursuit of goals and values the person regards as important (Sen, 1993). As Sen has pointed out, the capacity to transform information and other resources to action depends on individual characteristics, as well as social relations, the cultural context, and its norms.

The development of agency, therefore, can be viewed as a central sustainable objective of education (Tuomi, 2023b). This view contrasts with common skill- and competence-oriented views that typically conceptualize skills and competences from an instrumental point of view. In the instru-

mental approach it is natural to ask why a specific skill is useful and what it can be used for. Such questions, however, assume a closed world where the future unfolds according to a given plan, and innovation does not disrupt social and economic practices.

The capability-based model of agency and improved understanding of the ways in which agency can be distributed in AI supported environments can be argued to have fundamental importance for educational theories and policies in the coming years. Although there has been much research on these topics over the last century, technical developments in AI make earlier studies relevant in new ways. When the objective of education is viewed as the development of agency, the distribution of agency between human and AI agents becomes important also for the development of new pedagogic approaches.

### 4.2.3 Future of skills

Although education has many social functions, policy and societal debates often focus on the development of skills and knowledge that are useful for employment. The future of work is clearly also important for the development of education policies. Economists have great difficulties in measuring the labour market impact of AI (Frank et al., 2019), but it is widely accepted that AI will have a profound impact on labour market skill demand and composition (e.g., Arregui Pabollet et al, 2019; Brynjolfsson, 2022; Eloundou et al., 2023; Felten et al., 2023; Nedelkoska & Quintini, 2018; Servoz, 2019; Sostero & Tolan, 2022; Tuomi, 2018a).

AI will change occupations and job tasks in the coming years, perhaps more fundamentally than previously predicted. As was noted in the introduction, researchers from Goldman Sachs suggest that two-thirds of current jobs are exposed to AI-based au-

tomation. Influential earlier studies on the AI impact – conducted before the recent breakthroughs in generative AI – were based on the assumption that tasks that require communication and social interaction skills will be difficult to automate using AI (e.g., Autor et al., 2003; Frey & Osborne, 2017). Because of this, researchers have believed that AI will have a relatively minor impact in teaching occupations (Nedelkoska & Quintini, 2018).<sup>68</sup> Recent developments in large language models make such estimates of labour market impact obsolete, as AI is now widely used to support also non-routine cognitive tasks that require high levels of domain expertise.

Whereas most economic studies on the impact of automation and AI have used skill-biased and task-biased models of technological change, the development of data-driven AI systems requires data. It has, therefore, been suggested that ‘data-biased’ models of labour market change would be necessary to understand future skill demand (Tuomi, 2018b). Large language models can bypass this data bottleneck as they rely on human-produced texts available on the internet. It is clear, however, that more detailed analysis would be required to understand, for example, AI-induced changes in teaching practice and skill structures.

In general, well-established domain-specific skills become obsolete as a result of technical change. As new key technologies and general-purpose technologies emerge, new types of knowledge, skills, and experience become economically and socially important (Freeman & Soete, 1997; Perez, 1985). In practice, many prototypical skills of the last century were mirror images of

the existing production technology, and their content remained relatively stable as large-scale industrial production relied on standardization and automation. In this sense, the car, for example, generates the skills of vehicle maintenance engineer, and a computer creates a computer programmer (Tuomi, 2022). More generally, for each technical device, and the tools that are used to make it, it is possible to define the ‘skills’ of making and maintaining the device. Partly because of this, the current European Skills, Competences, Qualifications and Occupations (ESCO)<sup>69</sup> classification now includes over 13,000 skill definitions.

Although skills and competences are key concepts in policy development, the increasing importance of non-epistemic competence components (Tuomi, 2022) suggests that these concepts need to be reconsidered. There has been much effort in defining and characterizing 21st century competences and skills (e.g., Bellanca, 2010; EC, 2018; OECD, 2019a), but the links between learning theory and the concept of competence deserve further study.

In many discussions about skills, the underlying model of learning and knowing is what some educational theorists have called the ‘banking model’ of learning (Freire, 1972). In this model, knowledge is transferred from the teacher’s head, a book, or an adaptive computer system to the student’s mind, with the resulting skill and mastery as the outcome. In research on workplace learning analytics, this has been called the ‘knowledge-acquisition metaphor’ (Ruiz-Calleja et al., 2021). Knowledge is acquired but not created. In terms of the MATURE knowledge maturation model (Maier & Schmidt, 2015), the associated knowledge is structural in-

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68. For a critical assessment of this literature and a more detailed analysis of AI impact on teacher tasks, see Tuomi (2018a).

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69. <https://esco.ec.europa.eu/>

stead of emergent.<sup>70</sup> This model of learning that focuses on formalized, standardized, and culturally established knowledge, leads to a relatively static view on skills, at the same time allowing these skills to be defined, categorized, and classified. There are now many commercial AI-based tools that aim to support people in reflecting on their skills, locating skill gaps in the labour market, and guiding learners towards socially and individually useful career goals.<sup>71</sup> Skills data extracted from online job advertisements and other labour market data are now widely used to generate evidence for policymakers. As Buckingham Shum et al. (2022) note, these tools typically rely on predefined skills vocabularies.

Within constructivist models of learning, detailed domain-specific skill definitions, in general, might not always make sense. At the level of individuals, accommodation to the external reality plays an important role in Piaget's theory of learning, but Piaget also emphasized that knowledge is a relation between the knower and the observed reality. Learning changes both the learner and the observed environment (Furth, 1981). In such a Piagetian constructivist view, the prototypical concept of 'skill' is just a passive reflection of a given reality, in this case fixed by external social and industrial interests. The prototypical concept of skill can then be understood as a static artefact generated by historically established methods of collective production. Such a

conceptualization of skills and competences has limited relevance for learning, understood as development. As long as workplace routines and practices do not change, this conceptualization may be useful. When innovation and knowledge creation become important for organizations, or when there are disruptive technological changes in the economy, traditional skill-based labour market policies may become misleading and less useful than before.

The debate on whether education is for human development or to produce economically useful skills is an old one. Large corporations have addressed the proliferation of skills and related expertise by developing competence and knowledge management systems since the mid-90s (Tuomi, 1999), but it is also well-known that, in parallel, in empirical surveys business executives state that they are looking for employees with generic competences. These include competences in team-working, creativity, communication, problem-solving, and learning. An important question is how such skills can be assessed (Martinez-Yarza et al. 2023; Lucas, 2022) and linked to learning objectives and whether they should be credentialed and certified (Tuomi, 2022).

### 4.3 Learning analytics and new forms of assessment

In learning analytics, the use of AI-based pattern detection will provide new, increasingly advanced ways to support continuous formative assessment for learners and also a better understanding of learning processes for teachers and researchers. This will potentially lead to important breakthroughs in learning sciences. Much of our current knowledge about learning is based on labour-intensive data collection and self-reporting that can only provide limited access to learning processes. Better understanding

70. The knowledge maturation model distinguishes emergent and generally accepted types of knowledge. It suggests that learning occurs in the continuum between guidance, where established knowledge is learned by novices, and emergence, where more expert collaborate in creating knowledge. A similar distinction underpins the 5-A knowledge creation model in Tuomi (1999). For a useful review of organizational knowledge creation initiatives in the EU framework programmes, see Ley (2020).

71. An example of this approach is the CareerBot developed by HeadAI in collaboration with the Finnish Metropolitan Universities of Applied Sciences. It uses AI-processed skills data to help students find personalised study paths (<https://headai.com/careerbot-guides-students-towards-optimal-job-market-fit/>)

of learning can be expected to lead to new architectures for AI-based learning support systems and new pedagogic and andragogic models.

### 4.3.1 AI-supported formative assessment

Assessment plays two quite different roles in education. Summative assessment is used to validate and certify learning, and to compare and sort learners and educational institutions. Formative assessment, in contrast, aims to provide feedback to the learner and improve learning. Formative assessment has been challenging because it needs to be tailored for the present state of each learner. While standardized tests can be used to compare students and the knowledge they have accumulated, formative assessment measures individual progress on often idiosyncratic learning paths.

Until recently, assessment has been seen as a natural task for AI-supported automation. Marking tests and homework represents a large workload for teachers, and it has commonly been expected that AI could reduce this effort (e.g., Baker & Smith, 2019). Much of the visible and invisible work of teachers is concerned with formative assessment. Autograders are now widely used for assessing homework in computer science classes (e.g., Hsu et al., 2021; Nurminen et al., 2021), and Automated Short Answer Grading (ASAG) systems have gained increasing attention as data-driven AI has gained traction (Haller et al., 2022). Computer-based assessment of student essays was already expected to be imminent half-a-century ago (Page, 1966), and, with some delay, automated essay scoring (AES) has now become a vast field of research and a thriving industry (Belgman Klebanov & Madhani, 2021; Ke & Ng, 2019).

Assessment profoundly shapes pedagogic practices, the organization of work in educational institutions, and policy. The data that are collected in assessment and the types of learning processes that are assessed influence both learning and the development of education. Emerging technologies will generate new types of data that could be used in assessment, and both old and new data sources can be used in novel ways in the emerging landscape of learning.

Over the last decades, assessment practices have increasingly been based on evidence-centred design of assessment (Mislevy, 2018). This is a data-oriented approach that has been inspired by object-oriented software analysis and design methods (Mislevy et al., 2012). Evidence-centred design (ECD) starts from domain analysis, which leads to a domain model that conceptualizes the domain to be assessed. ECD emphasizes the specification of the logic of assessment, expressed in an ‘assessment argument’. The assessment argument describes what observable behaviours or performances should reveal the constructs of interest. A ‘conceptual assessment framework’ then makes the linkages between assessment tasks and evidence about proficiency explicit, linking a student model, an assessment task model, and an evaluation model. Based on these conceptual structures, the actual assessment instruments and test items can then be defined and delivered to the students. Evidence-centric assessment therefore defines the types of evidence and data that are collected to assess learner proficiency. When learning occurs on digital platforms, these data can also be collected on learner activities as a ‘side effect’ (DiCerbo & Behrens, 2014). This is sometimes called ‘stealth assessment’ (Shute & Ventura, 2013).



In future-oriented visions of education, adaptive learning systems are often presented as a technology that can relieve teachers from the tedious tasks of marking homework or even at times replace the teacher making continuous formative assessment possible. More importantly, continuous feedback could also improve learning outcomes. The need to explicitly design assessment tasks and link them to progress in learning also makes the objectives of instruction explicit. For example, knowledge-based intelligent tutoring systems require explicit models of what counts as evidence of learning, thus clarifying the objectives and goals of instruction (Luckin, 2018, p. 121).

A challenge found in this approach is that system designers often have a very simplified understanding of the complexities of the socio-technical environments where automation is introduced (Cerratto Pargman et al., 2023; Selwyn, 2022a). Much of the research on human-computer interaction and computer-supported collaborative work since the late 1980s addressed this challenge by turning to ethnographic methods (e.g., Bannon & Bødker, 1991; Nardi, 1995; Star, 1996; Suchman, 1987). The focus in these studies was on observing actual work practices instead of defining them based on abstract models of what people were supposed to do. Failures in automating organizational work processes were frequently shown to result from inadequate understanding of the concrete situations where people work.

For example, although marking homework is an onerous task, it is also an important activity for the teacher to gain insight into the students' learning and development. Homework does not only inform the teacher about the proficiency of a student; it also gives the teacher feedback on the student's emotions, attitudes, areas of missing

knowledge and skills, and other contextual factors. Total automation of grading can therefore have a negative impact on the teacher's capacity to teach. Effective instruction requires that also the teacher is continuously learning, and automation may inadvertently cut the teacher off from the learning loop.<sup>72</sup>

A five-year vision for the future of assessment, outlined by the UK digital technology and education agency Jisc (2020), suggests that assessment needs to become more authentic, accessible and inclusive, appropriately automated, continuous, and secure. Authentic assessment means, for example, that instead of measuring practical skills using pen and paper, they are measured in more realistic contexts, for example by using simulations with immersive technologies depending on the subject matter. Similarly, project-based assessment can move away from traditional pen and paper tests and essay-based assessment and evaluate the outcomes of the project. Appropriately automated assessment, according to Jisc, retains critical elements of student-teacher interaction, relieving teachers from the marking workload and improving the feedback students receive. According to Jisc (2020, p. 17), AI and learning analytics might be used to provide students with a personal learning assistant that continuously assesses student progress and helps in formative development, and it could make some 'stop-and-test' assessment points redundant.

72. Similarly, the visions of 'personalised' learning are often excessively individualistic and miss key learning processes. Personalised learning systems may cut the learner out of social interactions and relations that can be crucial for educational and life outcomes. Individualistic learning models often neglect the importance of socialization (Biesta, 2015), peer learning (Kimbrough et al., 2022), and teacher-student relations (Guilherme, 2019). In some countries, education is also important for the development of social capital, which is reflected, for example, in the high costs that students and their parents are willing to pay for access. Nardi et al. (2000), for example, argued that the motto of the Information Age is: 'It's not what you know, but who you know'.

A recent critical review of extant AI-supported assessment approaches suggests several ways in which AI could change assessment practices (Swiecki et al., 2022). First, it is possible to reduce the onerousness of assessment by automated assessment construction, AI-assisted peer assessment, and writing analytics. Second, AI makes it possible to move from ‘stop-and-test’ assessment that at best provides discrete snapshots of task performance, towards continuous formative assessment. Third, AI techniques can be used to adjust assessment tasks to the student’s abilities and personalize assessment. Fourth, AI can be used to generate increasingly authentic assessment situations, for example by using simulations. AI can also be used to collect and analyse data from authentic and complex assessments that may be difficult for humans to assess. Fifth, as AI itself is increasingly being used by the students and in work tasks, new assessment practices need to incorporate AI tools in the assessment designs.

Generative AI has been declared to particularly threaten essay-based assessment. As soon as GPT-3 and ChatGPT were released to the public several university professors around the world reported that they were able to detect AI-produced content in student homework. An anonymous poll at Stanford University, conducted in early January 2023, suggested that almost one-fifth of students had used ChatGPT in their final exams (Cu & Hochman, 2023). Several school districts and universities around the world quickly banned the use of ChatGPT, university honour codes and ethical guidelines were rapidly revised, professors changed assessment practices, and tools to detect and fingerprint AI-produced content were developed, sparking worries about a new technological arms race between generative AI systems and detection tools.

At the same time, it has been pointed out that ChatGPT makes it urgent for educators and institutions to reimagine their approaches to assessment, for example ‘replacing exams or other assessments with in-person assessments or altering the types of questions or exam formats that are used’. (Sabzalieva & Valentini, 2023, p. 13). Academics in higher education now compete for student attention using grades as both carrot and stick (Carless, 2023). Against the quick first reaction of banning AI from schools, it was suggested that teachers should embrace AI, and integrate it into their teaching. For example, the capability of ChatGPT to provide fast feedback to the student while working on projects, instead of providing conventional feedback after the project has been completed, was seen as an opportunity.

From a learning theory point of view, these debates on the threats and opportunities of AI-supported assessment highlight a shift from summative to formative assessment. Along the spectrum of assessment, intelligent tutoring systems that rely on fine-grained learning analytics are in one end, with almost continuous observation of student behaviour and progress. At the other end is high-stakes testing that aims to record learning outcomes. In the middle, there are now many suggestions that generative AI systems could be used as interactive learning companions that provide feedback to the learner (Sabzalieva & Valentini, 2023, p. 9). Some adaptive learning environments could also be found in this middle area.

As assessment is a major factor in shaping student learning, the above examples suggest that AI will have a profound impact on education in the coming years. To avoid automating outdated assessment practices using AI, it will be important to review and reconsider the assumptions that underpin existing assessment practices. As Swiecki



et al. (2022, p. 7) point out, AI-enabled assessment is not a neutral site where any form of learning will be detected and assessed. AI-enabled assessment will inevitably codify specific cultural, disciplinary, and individual norms, value systems and knowledge hierarchies. AI-enabled assessment may remain limited in its capacity to recognize learning that is creative and innovative simply because data-driven AI relies on detecting historical patterns (Tuomi, 2018a). The proposed pedagogical uses of generative AI, however, suggest that AI can become an important tool in re-designing assessment. Further research is therefore needed to understand what should be assessed, how assessment data should be collected and used, and how the new emerging forms of assessment could benefit learning and education.

From a technical point of view, automated essay scoring will probably make fast progress in the near future. This is because reinforcement learning from human feedback (RLHF), which is currently used to train large language models, can also be used to fine-tune language models for improved classification of essays. For example, criteria such as argument persuasiveness, specificity, and evidence (Ke & Ng, 2019, p. 6306) can easily be assessed by competent humans, and the results can then be used to fine-tune language models for essay grading. Beyond scoring, such models can also give the student detailed feedback on the reasons why the score is what it is and how the essay could be improved.<sup>73</sup> As mentioned before, policy action will play a key role in shaping the use of AI, also in assessment, with the proposed EU AI Act being a pioneer initiative in the field.

73. In reverse, improved essay grading can, of course, also be used to train generative AI systems such as ChatGPT, so that they produce higher-quality outputs. Improved assessment models, therefore, can also be highly important for the development of generative AI technologies.

### 4.3.2 Ethics of data-driven assessment

Continuous assessment generates large amounts of personal data. The development of new assessment methods therefore needs to address existing and emerging regulations and data policies. Ethics of learning analytics has extensively been discussed since the emergence of the field (e.g., Buckingham Shum, 2019; Buckingham Shum & Luckin, 2019; Hakimi et al., 2021; Pargman & McGrath, 2021; Prinsloo & Slade, 2017; Tzimas & Demetriadis, 2021) but data-driven assessment deserves further attention as multimodal data streams, data-driven AI, and XR become combined in the Next Internet.

With the advances of AI, machine learning and other emerging technologies, socio-emotional human-centred skills, such as leadership, communication, collaboration, empathy, etc. are becoming increasingly important and essential. LifeComp<sup>74</sup>, a European framework developed by the EC, has contributed to this area of research by providing a shared understanding of personal and social development competencies and has become a framework reference in supporting the development of life competencies as part of the curriculum (Sala, et al., 2020). More research is still needed to understand how to frame the learning objectives around these skills and how they can be supported and assessed (Martinez-Yarza et al., 2023; Lucas, 2022). A temporary moratorium on using data on these skills for machine learning systems has, therefore, been proposed until the social, educational, and ethical implications are clarified (Tuomi, 2022).

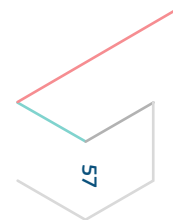
74. [https://publications.jrc.ec.europa.eu/repository/bitstream/JRC120911/lcreport\\_290620-online.pdf](https://publications.jrc.ec.europa.eu/repository/bitstream/JRC120911/lcreport_290620-online.pdf)



In technical terms, collecting data on ‘soft skills’ looks like a very similar problem to collecting data on student knowledge and other skills. A more detailed look at soft skills, however, also highlights the point that students are different, and addressing these differences is most often not feasible through simple educational interventions. In some European countries, policies try to respond to these differences through classroom-level differentiated education. In others, educational paths are differentiated based on expected educational achievement. AI systems introduce new ways to address the need to differentiate and personalize education, but as many socially and economically important skills and competences are linked to personality characteristics, in the future the appropriate unit of analysis for research on AIED and other educational technologies could be a technology-augmented learner (Tuomi, 2023a). For example, technology can potentially be used in support of neurodiversity and to augment capabilities in areas that are important for learning and individual well-being. We can use spell-checkers to support dyslexic students and text-to-speech technologies to support vision impaired learners. In a similar way, AI systems could be used to augment human learning capabilities when and where this is needed. It can be expected that as 21st century competences become more important, future AIED systems could benefit from such an augmentation approach.

Beyond the ethics of AI in education, where developmental considerations are central, education administrators also need to address AI governance from a regulatory point of view. At present, it is not known how the developmental and regulatory concerns should be combined and connected. This linking will be of special importance in educational contexts, but it should also inform

more general AI-related policy development. As suggested above, the development of the broader AI ecosystem will also shape the emerging educational landscape. Better understanding of the dynamics of ecosystem development is therefore also important for education policy development. This, in turn, could link industrial policy – understood here as the intentional structuring of markets and innovation processes – and educational policy in novel ways.



# 5 Conclusions and policy implications

Learning is at the centre of the ongoing transition from the Industrial Age towards what is commonly called the Knowledge Society. It should not come as a surprise that emerging technologies that shape learning, education, and knowledge creation have broad impacts beyond education itself. This report anticipates that a diverse range of technological innovations, which are currently at different stages of development, will complement each other and fuse digital, material, cognitive, and social realities in ways that we have not seen before. This calls for an unprecedented interlinking of educational, digital, environmental, and industrial policy, especially the regulation around the structuring of markets and innovation processes. The future of education itself needs to be viewed in this broader context of social, economic, and technical change.

This report looks at technology and society mainly from a European perspective, focusing on an area where access to new technologies is too often taken for granted. However, it should be noted that access is not universal within Europe and that, in any case, access itself is not enough to ensure competence, as we have seen in various studies during and following the Covid-19 pandemic (Cachia et al. 2021). Equity and access to high quality education is a priority for a transitioning Europe as it adapts education and training systems to the digital age, as outlined in the Digital Education Action Plan (2021-2027) (European Commission 2020) and two Council Recommendations published this year aimed at

ensuring universal access to inclusive and high-quality digital education and training (European Commission 2023a) as well as addressing the growing demands for digital skills triggered by the digital transformation of society and the economy (European Commission 2023b).

Digital technologies have a material basis and a significant societal and environmental impact that it is too easily overlooked. Climate change, demographic transitions, environmental concerns, and, for example, the growth of mental health problems among young people will shape the emerging landscape of education. Responding to those challenges, in 2022, the Council of the European Union (2022c) adopted new conclusions on the need to support well-being in digital education for both students and educators and the European Commission published a European Sustainable competence framework identifying a set of competencies that would help learners develop knowledge, skills and attitudes that promote learning on environmental sustainability (Bianchi et al. 2022). The challenges and opportunities of the twin digital and green transitions will require educational systems to adapt the curriculum and prioritise the development of new key competences.

New technical solutions are easy to adopt when they address pre-existing needs and support established practices. In this regard, technological innovation is often a conservative force, meaning that it is primarily concerned with the problems of the

past. It is therefore important to critically assess the potential of emerging and new technologies instead of hard-wiring obsolete practices. The future does not exist yet, and there cannot be facts about yet-to-be futures that could justify policy choices.

This is one of the reasons why policy development needs experimentation and exploration of imagined futures. These can be supported by knowledge and argument, but it should be noted that choices are always rooted on values. Visions of technological futures, therefore, should be accompanied with explicit discussion of ethics, which is a major priority in Europe. This report noted that a capability-based approach may be a useful starting point as it links developmental considerations central for education with the idea that individuals have varying capacities to translate resources to well-being. Technology plays a central role in this translation.

This report has suggested many areas where policy-related research and initiatives could be useful. Some key observations and results that also summarize potential areas for future work are highlighted below.

## 1. The Next Internet

The Next Internet will profoundly change the social and cognitive infrastructures of knowing, learning, and action. Over the coming decade, technological developments, including 6G networks, immersive technologies, and new distributed data and processing architectures will fuse digital, material, cognitive, and social realities in ways that we have not seen before. This creates opportunities to transform educational practices and institutions. The consequences of this transition are only very superficially understood today. Future-oriented policy-related research and development of educational use cases for this emerging world

would be needed to understand the implications of such developments. The ‘sensorization’ of wireless networks and their emerging capability to sense humans, action, and material objects in physical space links digital networks with the material world in radically new ways. Decentralized identifiers and distributed data structures will be important for the Next Internet, and the impact of these apparently technical developments on learning, teaching, and education deserves further research for a better understanding of what policy action would be needed.

## 2. Data

The amount of data on education and learning is growing fast. This provides opportunities for new pedagogic and andragogic approaches, as well as for the governance and management of education. Datafication of education comes with major ethical challenges and the development of evidence-based learning analytics and AI systems for education and learning requires careful balancing of opportunities and risks. Partly due to historical reasons, data on learning is now very fragmented across the Member States, and fine-grained data on learning processes have mainly been produced in isolated research projects and by large global platform providers, with limited visibility to educational stakeholders.

Although learning and education are central to the ongoing social, technical, and economic transition, data on learning and education has not yet received the level of attention it deserves, despite data being crucial assets that may enhance our understanding of the emerging landscape of education and for policy development more generally. The European Data Spaces could play a key role in this regard, by addressing learning and education as strategically im-



portant elements. Moreover, regular monitoring, evaluation, and assessment of enabling factors of digital education will also produce significant data on what is working and what is not, given most Member States still lack adequate structures to gather such data in some places (Cosgrove et al, 2023). In any case, while benefitting from learning and education data, it is essential to ensure the protection of children's rights and well-being (European Commission, 2021d).

### 3. Human-AI interaction in learning processes

AI is already influencing many educational processes and practices, with important implications for teaching, learning and assessment. Recent developments in generative AI suggest that agency can be distributed between AI-systems and human learners. Dynamic distribution of agency between learners and teachers is a key element in many influential learning theories, but it should be reinterpreted in the emerging technological context. Beyond theoretical interest, new models of technology-enabled learning and teaching could also form the basis for educational innovation and innovative designs of digital learning technologies. While it is important that the sector is able to allow innovation to take place, design and development of such models should also be regulated to ensure and protect children's safety, security, privacy and ownership (Cachia, et al, 2020).

### 4. Skills

As many as two-thirds of existing jobs will be exposed to AI-based automation in the coming years. This will generate a huge impact in education and vocational training. The resulting rapid changes in the labour-market will make the traditional concept of skill inadequate, both in education

and in labour-market contexts. This makes us question whether a broader understanding of competences is needed for curriculum development. Generative AI will refine digital skills, prompting policy makers to reconsider what is meant by digital skills. Transversal skills and human-centred competences, such as creativity, problem-solving, and socio-emotional skills are a result from the interaction between individual and contextual factors and not always easy to be replaced by technology. AI systems could play a vital role as an assistive technology, in support of a shift in education towards the development of skills that has been traditionally out of the formal curriculum. This makes us question whether a redefinition of digital skills is required, especially if we are to reach the target set by the Digital Compass (European Commission 2021a) and the European Pillar of Social rights Action Plan (European Commission 2021b) to have 80% of adults with basic digital skills and 20 million ICT specialists employed in the EU, with more participation by women.

### 5. Assessment

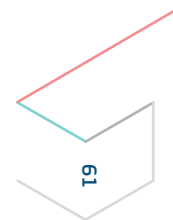
Assessment practices shape education and learning in fundamental ways. AI and learning analytics potentially enable new authentic, continuous, and learning-oriented methods of assessment. The emerging technologies discussed in this report could contribute to a decrease in the importance of summative assessment and 'teaching for test', as new digitally-mediated formative and continuous assessment approaches become more widely used. The development of these formative assessment methods, however, will greatly depend on existing and proposed regulations and available ICT infrastructures. The current technological landscape has also prompted debates on the relevance of assessment and the need for a better understanding of

how it will influence assessment in different disciplines, as the impact will probably vary widely across different subject areas. Developers in this area have themselves highlighted the need for regulation. In this respect, more research is needed to understand how AI, specifically generative AI, is affecting assessment and how it will affect transversal skills like creativity, critical thinking and problem solving. Beyond how educational organizations and systems assess students' achievement of intended learning outcomes, there are also relevant changes in relation to how learners can evidence the expertise they have developed with a high level of granularity. Digital credentials are not only replacing traditional paper-based certificates, but they also enable learners to gather evidences of their learning as they progress through their own learning paths. Micro-credentials may support life-long learning by certifying the learning outcomes of short-term learning experiences, but in order to reach their full potential it is essential to implement common standards to ensure their quality, transparency, cross-border comparability, recognition and portability; as established by the recommendation defining a European approach to micro-credentials adopted by the Council of the European Union (2022a).

## 6. The new trivium

Trivium and quadrivium formed the basis for education in the medieval Europe. The associated seven liberal arts – grammar, logic, rhetoric, arithmetic, geometry, music, and astronomy – were considered to be the foundational thinking skills. In the age of generative AI, core skills such as writing, mathematics, communication, and knowledge about the world, need to be rethought. For example, the 'writing synthesizer' hypothesis discussed in this report suggests that writing could soon involve genera-

tive AI systems in novel ways in the writing process, re- and deconstructing writing, and redefining what we mean by it. AI systems are already used in problem-solving, mathematics, writing human language and computer programs, and in visual arts and in music analysis and production. To understand the impact on educational practices, well-elaborated use cases are needed that show how generative AI could be used in various educational settings, and what policy implications such uses would have.



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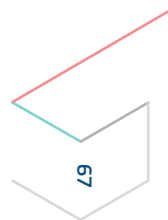
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# List of abbreviations and definitions

<b>5G</b>	Fifth generation mobile networks	<b>LA</b>	Learning Analytics
<b>6G</b>	Sixth generation mobile networks	<b>MOOCs</b>	Massive open online courses
<b>AES</b>	Automated essay scoring	<b>MR</b>	Mixed Reality
<b>AI</b>	Artificial intelligence	<b>OECD</b>	Organisation for Economic Co-operation and Development
<b>AIED</b>	AI in education	<b>OSD</b>	Open school data
<b>AR</b>	Augmented Reality	<b>PQC</b>	Post-quantum cryptography
<b>ASAG</b>	Automated Short Answer Grading	<b>QSL</b>	Quantum secure layer
<b>DIDs</b>	Decentralised identifiers	<b>RLAIF</b>	AI-automated reinforcement learning
<b>EBSI</b>	European Blockchain Services Infrastructure	<b>RLHF</b>	Reinforcement learning from human feedback
<b>ECD</b>	Evidence-centred design	<b>UNESCO</b>	United Nations Educational, Scientific and Cultural Organization
<b>EDC</b>	European Digital Credentials		
<b>EDM</b>	Educational Data Mining	<b>URIs</b>	Universal resource identifiers
<b>EU</b>	European Commission	<b>VC</b>	Verifiable credentials
<b>eIDAS</b>	Electronic identification and trust services	<b>VR</b>	Virtual Reality
<b>ESCO</b>	European Skills, Competences, Qualifications and Occupations	<b>W3C</b>	World Wide Web Consortium
<b>GDPR</b>	General Data Protection Regulation	<b>XR</b>	Extended reality
<b>GPT</b>	Generative pre-trained transformer	<b>ZKPs</b>	Zero-knowledge proofs
<b>IoT</b>	Internet of Things		
<b>ITS</b>	Intelligent tutoring systems		

# List of tables

**Table 1.** Chain of thought prompt with explanation.



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