Governing Artificial intelligence in the Higher Education Sector

Sociotechnical perspectives, regulatory challenges and working conditions

Edited by
Aída Ponce Del Castillo

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European Trade Union Institute (ETUI)

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Preface

Aída Ponce Del Castillo

Artificial intelligence in the higher education and research (HER) sector is situated at the core of the production of knowledge. It presents both opportunities and profound challenges particularly for academic work and labour rights. While AI-driven systems hold the potential to enhance teaching, research and institutional efficiency, they are also introducing new forms of algorithmic management, data-driven surveillance and the delegation of intellectual labour to AI-powered platforms, often without the input of those most affected: educators, researchers and academic staff.

AI in HER is not only a question of pedagogy or innovation. It is a question of governance and political economy: who designs and controls the infrastructures of teaching and research; who benefits from their deployment; and what happens to professional autonomy, academic freedom and labour rights when decision-making is delegated to the providers of data-driven platforms.

These technologies are far from neutral. AI-driven decision-making, algorithmic monitoring and the growing reliance on private sector educational technologies mirror and reinforce broader shifts in the power dynamics of production, academic governance, knowledge and institutional control.

This volume brings together a selection of contributions presented at the expert conference on AI at work: impacts on the higher education and research sector, held in Brussels on 28-29 February 2024. The conference was jointly organised by the European Trade Union Institute (ETUI) and the European Trade Union Committee for Education (ETUCE). Additional contributions on the conference themes further enrich this volume.

The conference brought together a multidisciplinary group of experts to make a critical examination of the implications of AI in higher education and research. Drawing on perspectives from communications and media studies, education, information technology, philosophy and law, the contributors explored the sociotechnical dimensions of AI adoption and its impact on job content, work organisation, professional autonomy and the rights of educators, researchers and university staff. Their analyses challenge the dominant techno-solutionist narratives and contribute to shaping future research agendas and policy responses.

In addition to the thematic inquiries, the conference examined the impact of a range of AI tools beyond traditional automation including machine learning and generative AI, as well as technologies that extend beyond campus-based environments such as immersive and extended reality. While these tools are often presented as enhancing academic efficiency, they are also reconfiguring the fundamental structures of higher education, shifting decision-making authority away from education institutions and staff to private technology providers. Some education platforms now integrate data-intensive features such as learning analytics, automated flagging and AI-powered assistants, which are becoming components of core products by default. These are frequently being rolled out without consultation, limiting the ability of institutions and trade unions to influence what and how digital tools are being used.

Key discussions addressed in addition the influence of AI systems on professional autonomy and the ways in which algorithmic systems are influencing working conditions. AI-driven analytics, automated grading and administrative AI tools are not passive instruments; they function as systems that can introduce new forms of control, reshape working conditions, intensify work and erode traditional forms of academic freedom and pedagogical autonomy.

The increased datafication of teaching and research enables the monitoring of staff activities through granular metrics which reinforce algorithmic management and surveillance, intensifying algorithmic oversight and 'productivity'. They also present unintended consequences, particularly in relation to academic labour, knowledge production and the institutionalisation of new forms of governance in the education system.

To reflect these critical issues, this book is structured around four thematic sections each addressing a key area in which the impact of AI systems is being most keenly felt in the HER sector. The contributions draw on a diversity of approaches, from the philosophy of technology to regulatory frameworks to trade union analysis. They examine the philosophical, sociotechnical, ethical, governance, legal and working conditions dimensions.

The volume opens with a contextual analysis of the evolving role of AI in the HER sector. The second part moves through a critical exploration of AI's sociotechnical applications and implications for educators, researchers and academic staff, in the process highlighting the specific challenges faced by all three groups particularly in relation to automated monitoring and decision-making. The third part addresses the governance and legal frameworks shaping AI in HER, including issues of data protection, privacy, fundamental rights, intellectual property, copyright and the implementation of the European Union's AI Act. Legal analysis shows the complexities surrounding intellectual property rights, particularly regarding the use of generative AI. The fourth part explores the concrete impact of AI systems on working conditions and professional autonomy, closing with a synthesis chapter with conclusions and recommendations. An afterword provides a critical reflection on the future of the sector, outlining several avenues of enquiry.

Rather than passively accepting AI as an inevitable and automatic path towards 'progress', the contributions in this volume critically examine how these technologies are reshaping the HER sector – redistributing power, restructuring work or redefining academic autonomy. In doing so, they highlight the need for more democratic, precautionary and worker-centred approaches to its design, development, implementation and governance, including transparent governance for platform adoption and data use. This would ensure that HER workers are meaningfully involved in shaping the education environments in which they work.

The analyses presented here offer practical and conceptual insights into how AI systems are designed, deployed and contested within the HER sector. The objective is not to reject technology but to call for a governance that matches the stake: to subordinate technological systems to the education mission and to ensure that innovation does not become a pathway to intensified surveillance, weakened autonomy and privatised control over knowledge work.

Part 1
Setting the context

Chapter 1
Understanding AI in higher education and research: what is at stake?

Aída Ponce Del Castillo and Martina di Ridolfo

Introduction

Artificial intelligence (AI) systems are undergoing rapid evolution, driving profound change across all levels of education. AI promises to redefine institutional structures, pedagogical approaches, learning practices and teaching methods throughout the sector.

This chapter provides an overview of AI integration in higher education and research (HER), encompassing both traditional AI systems and generative AI (GenAI). Immersive and spatial technologies have re-emerged as part of this trajectory. Extended reality (XR), understood as an umbrella term for virtual, augmented and mixed reality (Fernandes, and Hine, both this volume), is also being integrated into higher education for simulation-based teaching, virtual laboratories and remote collaboration. When these environments converge with AI-driven analytics and biometric tools, they become part of the same datafied infrastructure that is reconfiguring academic work.

The chapter synthesises recent scholarship on the field with particular attention to the dimensions that affect academic labour. Drawing on analyses of the commercialisation of the educational technology industry (EdTech) (Williamson and Hogan 2021; Komljenovic et al. 2023), critical studies of datafication (Williamson et al. 2020) and research on AI's impact on educators (Holmes and Porayska-Pomsta 2023; Watermeyer et al. 2024), it identifies three interconnected developments that have accelerated AI adoption: Covid-19's acceleration of digital transformation; the emergence of generative AI; and the proliferation of university-corporate partnerships. The contribution it makes lies in connecting these developments to demonstrate how AI integration in higher education constitutes a transformation of academic work itself, not merely pedagogical innovation. As described in the Foreword, this volume centres the worker perspective about AI integration.

This opening chapter provides the foundation for that approach by examining the structural context of European higher education and its relationship with technology; the three pivotal developments outlined above; the role of the EdTech industry in shaping this transformation; the impacts on academic working conditions and professional autonomy; and the governance frameworks, both regulatory and institutional, that are currently shaping AI deployment. Additionally, it identifies the critical gaps in research, policy and governance regarding how AI integration is affecting HER workers, thereby establishing the rationale for the sociotechnical, legal and labour analyses that follow in subsequent chapters.

1. Understanding technological integration within HER. Setting the context

The European HER sector exhibits structural diversity. It includes study and training programmes, tertiary education and training for research at post-secondary level. The sector comprises public and private institutions recognised through accreditation systems or by state authorities. These encompass universities of applied science and research universities, vocational training centres, research institutions and other institutes operating under the direct control of, administered by or associated with higher education establishments (UNESCO 1997, 2025; European Commission 2022). The European HER system remains characterised by significant differences in terms of institutional autonomy, funding mechanisms, the quality assessment of research and teaching, internal institutional governance (Capano and Pritoni 2019) and the changing role of the state in performance (Bruni et al. 2020).

The HER sector has been intertwined with technological advances dating from the conception of the foundational theories of artificial intelligence and the appearance of computers. The integration of technology into education began with computer-assisted instruction in the 1960s, which was designed to provide interactive learning experiences, offering personalised feedback and adaptive learning although with an uneven record of implementation (Hof 2023).

Over the decades, AI in education has evolved into a specialised academic field, artificial intelligence and education (AIEd), which continues to expand and shape pedagogical practices and student engagement (Bates et al. 2020; Komljenovic 2022; Oliveira, this volume). Luckin et al. (2022) categorise the uses of AIEd in three main groups in terms of who is expected to interact with them most directly: learner-facing; educator-facing; and systems for education administrators. While these categories provide a useful framework for understanding AIEd tools, overlaps occur.

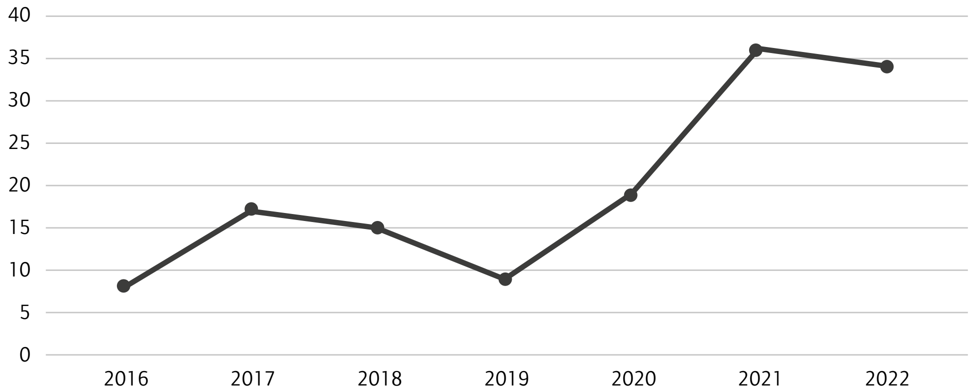
1.1 Integration of AI systems in HER: pivotal developments

Despite the deep-rooted connection of HER to technology, the integration of AI systems in the education sector has traditionally been slower than in other economic fields such as medicine, industry or finance (Salas-Pilco et al. 2022; Luckin et al. 2022). A range of factors has contributed to the 'one size does not fit all' for digital transformation such as the diversity of the infrastructure; the complex interplay between the types of technology, skills, pedagogy and the wider social and cultural context in which education operates; and, also important, the significant and upfront financial investment (Gkrimpizi et al. 2023). However, three key pivotal developments have accelerated the integration of AI systems in HER, reversing this trend (Crompton and Burke 2023). These are explored in the following three subsections.

1.1.1 Covid-19 as an accelerating agent

The first major catalyst was the Covid-19 pandemic which accelerated the global adoption of AI-driven educational systems, amplifying their role in teaching, assessment and student engagement. A systematic review by Crompton and Burke (2023) shows that, following a drop in 2019, the years of the Covid-19 pandemic (2020-2021) corresponded to a sharp spike in the use of AI systems in higher education and research. The trend stabilises with a plateau in 2022 which, it can be assumed, was influenced by the gradual resumption of in-person teaching and learning.

Figure 1.1 **Chronological trend in AIEd in HER**



Note: original graph is non-specific as regards the y axis labelling.
Source: Crompton and Burke (2023). Licence: https://creativecommons.org/licenses/by/4.0/

1.1.2 Fast adoption of generative AI

Building on this momentum, a second pivotal moment emerged with the rise and rapid integration of GenAI systems. The launch of ChatGPT, a conversational tool based on generative pre-trained transformer architecture, in November 2022 triggered a proliferation of varied GenAI systems tailored for or used in the education sector (e.g. Copilot, Consensus, Gemini, Elicit, Scite, ChatPDF). GenAI systems have been incorporated into education practice far more rapidly than previous technological innovations in the light of two key features: their cross-sector applicability (as a form of general AI); and that they are easy to access and use. Indeed, the most widespread GenAI tools do not require significant hardware capacity – from an end-user perspective – to be accessed and used; they can be installed as simple apps and, in some cases (such as ChatGPT) are even available through widely used platforms like WhatsApp. Moreover, many of these tools can be used without the need for authentication and are applicable across virtually all domains.

These characteristics have enabled a bottom-up adoption process by students, academics and university staff. In 2023, a collaborative initiative involving 19 universities in United States and Canada developed the 'Generative AI Product Tracker' which systematically tracks and evaluates over 100 GenAI tools specifically marketed towards postsecondary faculties or students, or higher education, in teaching, learning and research activities

(Baytas and Ruediger 2024).[1] This widespread adoption also prompted European HER institutions to reassess the long-term implications of AI systems for the sector, leading to discussion on the guidelines and boundaries for ensuring their responsible use in academic teaching, learning and research (UNESCO 2023).

When examining the current use of AI systems in higher education, it is evident that, apart from a few small-scale national reports, cross-national comparative studies remain limited. This makes it challenging to obtain a detailed, systematic understanding of how AI is being used in practice within education institutions across Europe. Despite this gap, a literature review indicates that AI applications in use include automated grading and assessment systems, plagiarism detection and AI-authorship identification tools, personalised learning recommendation systems, intelligent tutoring systems and generative AI applications such as chatbots and virtual assistants for instructional support, as well as AI agents (Zawacki-Richter et al. 2019; see also the Annex in this volume).

The adoption of GenAI thus reflects a qualitative shift: AI systems are no longer an accessory or auxiliary but are becoming deeply embedded in higher education institutions. The scope of this embedding is, in addition, extensive. These technologies are permeating core academic functions and promising to serve diverse purposes including automated test generation, lesson planning, student performance assessment, feedback provision, learning outcomes predictions and adaptive instructional design (Crompton and Burke 2023; VUB 2023). From a research perspective, they also involve data analysis, the production of summaries, abstracts and tables of contents, and support ideation, grant application development and reporting.

This pervasive integration, however, merits critical scrutiny. One of the most advertised promises – the saving of time – lacks robust evidence (Galanos 2024a). More fundamentally, the deployment of AI systems risks exacerbating the metrics-oriented culture concerning how academic work and workers are measured (Galanos 2024b; Gould 2024). When AI systems are designed to optimise measurable outputs – assessment scores, publication counts, student throughput – they inevitably marginalise the qualitative and nuanced dimensions of teaching, learning and scholarship that resist quantification. This creates a feedback loop: institutions adopt AI to improve their metrics, thereby reinforcing their primacy and, in the process, further entrenching a reductionist understanding of academic value.

1.1.3 University-industry partnerships

Alongside the technological transformations brought by Covid-19 and generative AI, the proliferation of formal partnerships between universities and technology companies is also reshaping the sector's trajectory (Wegemer 2025). These partnerships are often presented as innovations in education, drivers of new knowledge and enablers of medical or technological solutions. However, beneath this narrative lies a fundamental

1. The Generative AI Product Tracker is publicly available. https://sr.ithaka.org/our-work/generative-ai-product-tracker/

question about institutional autonomy and the terms on which universities engage with proprietary AI systems.

The scale of corporate integration is considerable. OpenAI's NextGenAI is a consortium including 15 leading research institutions across the world (OpenAI 2025). In Europe, multiple prestigious institutions have adopted ChatGPT Edu, a version of ChatGPT tailored for higher education, including Oxford University in the United Kingdom (UK), Sciences Po in France and IE University in Spain; all staff (academic, research, support and administrative) and students have access. Parallel partnerships are emerging with Anthropic, the developer of Claude, through the Claude for Education initiative, which includes the London School of Economics and Northeastern University in Massachusetts.

Meanwhile, Denmark offers a contrasting model that prioritises public control and cultural sovereignty. The universities of Copenhagen, Aarhus and Southern Denmark have established the Danish Foundation Models, a collaborative initiative involving Danish universities and research organisations that is investing in a national infrastructure for the open source development of Danish language tools (Danish Foundation Models 2025). Rather than ceding ground to the proprietary systems controlled by foreign corporations, these institutions have chosen to build publicly accountable AI infrastructures that preserve linguistic and cultural specificity.

This divergence highlights a critical choice that all institutions are having to face. The corporate partnership model provides rapid access to cutting-edge technologies but creates dependencies on proprietary systems whose governance, data practices and development priorities lie outwith institutional control. The public infrastructure model requires substantial collective investment and slower deployment, but might better preserve institutional autonomy; it also enables transparency and ensures that AI development serves public education missions rather than commercial objectives.

What is at stake extends beyond technical capabilities to institutional governance and academic autonomy. Corporate partnerships are becoming the predominant model, with public infrastructure approaches remaining exceptional. This bifurcation raises fundamental questions about institutional control over core academic functions, the viability of public alternatives and the sustainability of academic independence in an increasingly AI-dependent sector. These dependencies are not primarily addressed by the product safety architecture of the European Union's AI Act which focuses on the conditions for placing and using AI systems on the market rather than on market power, platform intermediation or lock-ins.

Moreover, these three developments – the accelerated adoption of digital tools during Covid-19, the generative AI revolution and university-industry partnerships – have created fertile conditions for commercial actors; that is, the EdTech industry.

2. The EdTech industry: commercial dynamics and market consolidation

The widespread integration of AI systems during the Covid-19 pandemic also fuelled the growth of educational technology. EdTech is mainly driven by private-led industry and venture capital aiming at scalable investments (Komljenovic et al. 2023; Komljenovic, this volume). The growing role of EdTech reflects the increasing privatisation and commercialisation trends within the HER sector, such as market-based competition and performance metrics, data commercialisation, control over academic intellectual property and data surveillance (Williamson and Hogan 2021).

The scale and pace of EdTech expansion are considerable. Between 2020 and 2022, European EdTech experienced a sharp acceleration in investment activity, culminating in a peak of €1.64 billion in venture funding in 2022, reflecting Europe's growing weight in the global EdTech landscape (Global EdTech 2025). In 2024, the European EdTech market was valued at 40.86 billion euros (Market Data Forecast 2025). This expansion is expected to continue, with the market projected to grow to 89.79 billion euros by 2028, at a compound annual growth rate of 14.97% (Focus Reports 2023). A recent mapping published by the Edtech Alliance in September 2025 collected more than 1,660 European Edtech organisations. This rapid growth of the market is not solely driven by increased use of AI systems; it also reflects a strategic shift in political priorities at both national and European levels.

At national level, several governments have launched initiatives to integrate such technologies. For instance, France's Plan numérique pour l'éducation, the UK's EdTech Strategy and Germany's DigitalPakt Schule support the integration of EdTech in higher education and research (Focus Reports 2023). In line with this trend, the Organisation for Economic Co-operation and Development (OECD 2024) reports that 88% of education ministries are now prioritising the integration of digital technologies, including AI, into daily life and work. These national strategies signal a shift in how governments are conceptualising the education infrastructure, viewing EdTech partnerships as vehicles for economic competitiveness and possibly for digital sovereignty too.

This is also evident in European Commission policy. In its Communication on the Union of Skills, the European Commission (2025) announced a closer cooperation with EdTech, stating that 'a robust EU digital education ecosystem will prepare for the future and establish long-term partnerships with EU-based EdTech and independently developed European solutions.' This priority emphasises the Commission's commitments towards innovation and market competitiveness, which raises concerns about the potential transfer of control over education tools and infrastructure from public institutions to profit-driven technology companies, amidst other long-term implications.

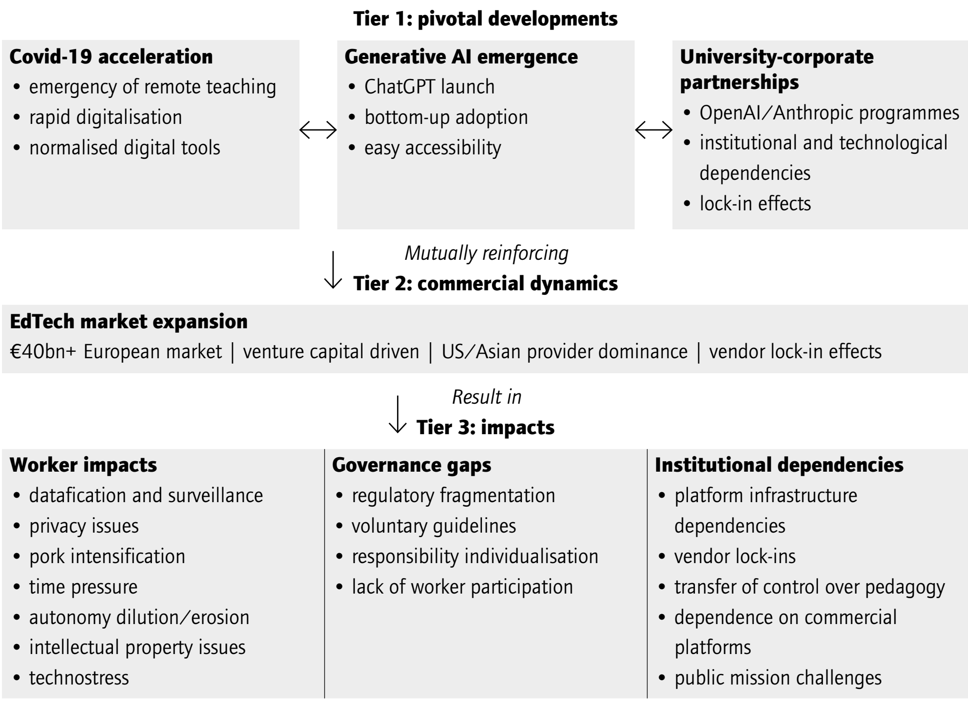
Moreover, a gap exists between policy ambitions and market realities. Despite its growth, European Edtech still remains fragmented across national education systems in light of the variety of regulations, curricula and languages which keep European education systems heavily reliant on key American and Asian players such as BYJU's, Blackboard, Chegg, Coursera, Edutech, Google and Microsoft (Market Data Forecast

2025). This dominance by non-European Union (EU) providers, even as the European EdTech sector expands, exploits market fragmentation across national systems.

The result is a paradox: European policy promotes EU-based solutions while European institutions continue to integrate predominantly American EdTech systems, embedding dependency on commercial platforms developed according to governance models, pedagogical assumptions and data practices that may not align with European regulatory frameworks or educational values.

Figure 1.2 illustrates how the three interconnected developments explored in this chapter have converged to drive EdTech market expansion. This expansion, in turn, generates three categories of impacts: direct effects on academic workers' conditions and autonomy; governance deficits in regulatory and institutional frameworks; and institutional dependencies on commercial technology providers. The double-headed arrows indicate that these developments are mutually reinforcing.

Figure 1.2 **Three pivotal developments and their impacts on higher education and research**



Source: authors' own design.

The consequences of this EdTech-driven dependency appear throughout this volume. The chapter by Copeland on the key AI issues for trade unions in higher education and research shows how this is affecting academic freedom, intellectual property and workload. It also identifies an agenda for collective bargaining and social dialogue as an essential governance step. The chapters by Elora Fernandes, on XR-driven environments that capture sensitive data, and by Emmie Hine, who describes the impacts on those affected, examine how these institutional dependencies are extending into immersive teaching and research. In addition, they show how commercial platforms are structuring data flows and shaping how bodies, gestures and effects are being monitored and governed.

3. Impact on working conditions in the higher education sector

This section examines how AI integration is affecting academics, researchers and administrative staff, focusing on dimensions that have received insufficient attention in both research and policy discussion.

3.1 The missing worker perspective

The institutional transformations outlined above are reshaping not only university governance and educational delivery, but also the daily realities of academic work (Copeland, and Komljenovic, both this volume). Researchers have extensively examined AI's pedagogical applications and institutional strategies, focusing on the educator and learner-centred aspects and emphasising AI's role in enhancing teaching methodologies and the optimisation of learning processes through system-supporting models (Zawacki-Richter et al. 2019; Holmes and Tuomi 2022; Holmes and Porayska-Pomsta 2023; Holmes et al. 2022). However, far less attention has been paid to what impact these technologies are having on academics, researchers and administrative staff, in particular their professional autonomy, working conditions, labour rights and wellbeing.

Nevertheless, while AI integration to support student learning is well-represented, governments are placing less emphasis on AI-enhanced professional learning for educators, while the investment in AI for their support remains significantly lower than for student-focused AI applications (OECD 2024). In response, the OECD is calling for a shift towards educator-driven innovation in which educators are the co-researchers, co-developers and co-evaluators of AI tools.

3.2 Shifts in professional autonomy and academic control

AI systems are moving from support roles to determinative functions. This implies issues related to governance and control, implementation and the resulting dependency on digital platforms (Burnett and Harvey 2023). As AI expands from 'assistance' and support to automated decision-making, it is increasingly shaping curricula, assessment methods and academic decision-making. As Komljenovic (this volume) demonstrates, this growing reliance on data-driven solutions for grading or curriculum design raises concerns about bias and discrimination, transparency and surveillance, and restricted academic freedom and pedagogical autonomy.

Furthermore, the adoption of AI tools is often shaped by a wide range of stakeholders including government, local authorities, institutional leaders, senior educators, individual educators or even students (Luckin et al. 2022) and, of course, the EdTech industry. However, a technology-focused perspective often overlooks the influence of those who design these tools, as well as the market-driven forces that are steering their development. This narrow perspective risks giving control over education practice to external private actors, thereby challenging the professional autonomy of educators and other academic staff.

Oliveira (this volume) shows that digitalisation is already reshaping pedagogical thinking and the teaching profession, raising similar questions about how far such tools should steer education practice. Professional autonomy in higher education encompasses more than freedom from direct supervision; it includes the capacity to exercise professional judgement about pedagogical and assessment methods. According to the Organisation for Co-operation and Development (OECD 2024: 86), educators need to be equipped not just with digital skills but also with an evaluative mindset towards a critical integration of AI and a consideration of its pedagogical value. This requires moving beyond instrumental digital competencies to cultivate critical agency: the capacity to assess technologies' pedagogical value and determine which tools to embrace and the conditions in which to do so.

3.2.1 Datafication, surveillance and the erosion of privacy

AI systems fundamentally depend on data, and their integration necessarily involves extensive data collection from students, academics and researchers. This vast and systematic collection of personal data raises questions of how those data are managed and shared both inside institutions and outside with third parties. The use of this data is wide-ranging and exhibits a diversity of purposes encompassing staff surveillance, work performance and individual or collective benchmarking (see Fernandes, this volume). The metrics on which data are collected raise several issues related to what is measurable or assessed and the quantitative criteria used.

Building on Williamson et al. (2020), the intensification of quantification not only defines what is visible or left invisible, it attributes value and induces judgement, possibly in arbitrary ways mostly because not all forms of teaching can be quantified and analysed. The risk of datafication is pedagogic reductionism 'as only that learning that can be datafied is considered valuable' (Williamson et al. 2020: 358).

Moreover, surveillance practices are proliferating and now encompass online class recordings, facial recognition or facial expression analysis for university interviews or the management of academic productivity (Adams 2025; QAA Scotland n.d.). These systems amplify concerns about control, bias, workplace privacy, professional autonomy and academic freedom. When universities adopt proprietary AI systems through corporate partnerships, data governance becomes complicated by commercial interests.

At the same time, XR technologies are amplifying these surveillance concerns by enabling even more granular data collection on attention, engagement, physical movement and behaviour, whilst also raising distinct questions about the cognitive impacts on those who use these immersive systems (Fernandes, and Hine, both this volume).

3.2.2 Work intensification and professional wellbeing

AI integration is frequently justified on efficiency grounds: in principle, by automating routine tasks, AI should free academics to focus on higher-value activities. However, rather than reducing workload, AI tools often contribute to work intensification and shape overall wellbeing.

Digital technologies can exacerbate exhaustion, anxiety and stress among educators (OECD 2024: 85). AI integration adds specific pressures: studies report that digitally enabled remote work, ramped-up during the Covid-19 pandemic, has further increased the work burden with academics reporting not only increased perceptions of insecurity and overload, but also chronic fatigue and decline in physical and mental health (Decataldo and Fiore 2022; Watermeyer et al. 2024). Beyond the effects on health and wellbeing, Bencsik and colleagues (2021) find that factors associated with technostress can undermine innovation and negatively affect users' perceived work performance, satisfaction and commitment.

The problem is connected to the metrics culture: where AI systems enable more granular quantification, institutional expectations may grow accordingly. Also, if AI tools make it technically possible to grade more assignments or respond to more queries, pressure also grows. The result is workload expansion, not reduction.

4. Governance approaches: regulatory frameworks and institutional responses

The sections above highlight the numerous governance issues shaping AI deployment in European higher education, to which this section turns. Who determines how AI systems are deployed in education institutions? What protections exist for academic workers? What rights do they possess to information and consultation regarding AI implementation?

In the EU, technology is governed though a multiplicity of approaches. The General Data Protection Regulation, although it follows a risk-based approach, puts the focus on the data subject and the rights thereby accrued. The AI Act (Ponce Del Castillo, Kivinen, and Mäntysaari, all this volume), also adopting a risk-based approach, puts its focus on innovation and competitiveness. The Digital Services Act sets due diligence and transparency obligations for intermediary services and online platforms, with additional systemic risk governance duties for very large online platforms and very large online search engines. The Digital Markets Act targets the gatekeepers controlling core platform services with the aim of reducing structural dependency and improving contestability for business and other end users. These form a web of interrelated frameworks, targeting different aspects of technology. Despite this overarching infrastructure, it is challenging to provide individuals or users with meaningful control or adequate information to understand the impacts that automated decisions are having on them.

Governance is essential to ensure the lawful deployment of AI tools in education. The European Commission recognises AI's potential risks in education and in education pedagogies. However, the AI Act does not fully address the spectrum of concerns that goes beyond accessing education and assessing or evaluating learners in education. The AI Act's regulatory approach, anchored in the legal basis of the internal market, is not intended to protect human rights within education and the impact of AI on educators, students and pedagogies. The labour dimensions highlighted above fall outside the AI Act's scope.

Acknowledging the need for improved protection, several attempts have been made to fill in these gaps (Kivinen, and Mäntysaari, this volume). In 2022, the European Commission developed ethical guidelines on the use of AI and data in teaching and learning to support educators and school leaders in critically using AI tools while addressing possible risks. At international level, the 2021 Recommendation of the United Nations Educational, Scientific and Cultural Organization (UNESCO) on the ethics of artificial intelligence articulates a framework underpinned by the protection of values and principles as well as actionable areas for policymakers.

Nevertheless, this proliferation of regulatory initiatives, while popular and well-intentioned, are characterised by heterogeneous theoretical approaches and conceptual ambiguity (Ponce Del Castillo, this volume). Four drawbacks should be flagged: (1) many of these frameworks fail to make explicit the ethical principles underpinning their recommendations (Mantelero 2022), which further complicates efforts to operationalise them; (2) they frequently overlap between legal norms, leading to confusion regarding the respective roles of ethics and law (Robles Carrillo 2020); (3) as Wagner (2018) argues, this overlap represents a dangerous pattern as the absence of a binding framework creates accountability and liability gaps, posing potential risks to individuals and weakening the protection of their human rights, particularly for vulnerable categories; and (4) they are voluntary, meaning that, if not complemented with mandatory legal instruments, they are not sufficient, by themselves, to guarantee the adequate protection of human and fundamental rights (Scherer 2016). Moreover, the existing sectoral and legal approaches towards AI systems translate into a de-formalisation and fragmentation of the legal system itself (Krausova 2017; Collins 2019). Without enforceable mechanisms, the governance deficit persists, regardless of well-intentioned recommendations.

4.1 Institutional responses: decentralised governance of generative AI

The emergence of GenAI has further complicated the governance landscape. While students have embraced AI-powered tools, the proliferation of generative AI applications is causing prominent challenges to academics and researchers in terms of academic integrity as well as pedagogical and academic relevance.

In response, most universities have developed their own governance approaches through policies and guidelines on the integration and/or permissible use of GenAI. Although they vary in tone and approach, most adopt an open perspective framing GenAI as an opportunity to adapt learning and to support curriculum guidance or lesson planning in view of technology developments (Luo 2024; Wang et al. 2024; Jin et al. 2025; McDonald et al. 2025), while recognising the limitations of a technology that is in constant evolution.

Institutional policies exhibit considerable variation. For example, the programme Responsible AI at Stanford University,[2] indicates that 'instructors may not ban student use of AI tools for take-home coursework, including assignments and exams, but may choose whether to allow student use of AI tools for in-class work'. Furthermore, the Stanford Honor Code states that 'in particular, using generative AI tools to substantially complete an assignment or exam (e.g. by entering exam or assignment questions) is not permitted' (Stanford University 2023). Leicester University (2024) indicates that 'Generative AI can be an important tool to support the process of assessment. Schools will make clear to students what, if any, role AI can play for each assessment it conducts'. From a research perspective, Vrije Universiteit Brussel (VUB) in Belgium states that '[t]he VUB is open to using AI tools for various research purposes and imposes few specific restrictions' (VUB 2023).

These examples not only illustrate the variation in institutional approaches and interpretations, but also show how universities find themselves at a crossroads in the desire to adopt innovative tools but falling short of addressing the important subsequent issues.

The first problem is the decentralisation of responsibility. Rather than establishing clear institutional frameworks, universities frequently leave determinations of appropriate or ethical AI use to individual departments (Wang et al. 2024; Jin et al. 2025; McDonald et al. 2025). This creates predictable problems: confusion about permissible use, increased risk of unintentional violations and accountability gaps.

Second, the substantive issues are receiving inadequate attention. Gaps remain in tackling issues related to data privacy, intellectual property, copyright materials, quality and accuracy of outputs, misuse and equitable access to these tools (Jin et al. 2025; McDonald et al. 2025), but also in developing guidelines that effectively tackle these risks in a way that goes beyond mere caution. The focus remains overwhelmingly on regulating student use, with far less consideration given to the data generated about academics themselves. What remains absent is serious engagement with how AI integration is reshaping pedagogical practices, altering the nature of academic labour and affecting professional autonomy.

To address these gaps and challenges, the HER sector requires moving from fragmented approaches to more robust and well-defined frameworks adaptable over time (Jin et al. 2025). These should not only prioritise use and support academic integrity and educational needs but also equip academics, researchers and administrative staff with awareness and critical literacy. Reigeluth (this volume) complements this by arguing for a form of technical culture that allows educators to understand, question and repurpose

2. Responsible AI at Stanford. https://uit.stanford.edu/security/responsibleai

AI systems instead of being reduced to compliant users. This can safeguard their rights and enable their agency while shaping how these AI tools are used in the HER sector.

However, formal frameworks and soft law are not enough. Weinberg and Ovetz (this volume) show how academic workers and students can organise to scrutinise AI deployments, contest harmful uses and press institutions to respect rights and negotiated limits.

Conclusion

The integration of AI systems in European higher education poses substantive challenges to professional autonomy, academic freedom and working conditions. These changes do not only concern text based, visual or back office AI tools. When AI is combined with XR environments, it can track bodies, gestures and movement in space, bringing datafication into classrooms and laboratories too.

Three moments have been pivotal in embedding AI deeply within the higher education ecosystem: Covid-19's acceleration of digital transformation; the emergence of generative AI; and the proliferation of university-corporate partnerships. Policy frameworks focus on AI's pedagogical potential, but far less attention is being directed to addressing how these technologies are reshaping academic work itself. Much of the existing debate on AI in higher education centres on students; however, this chapter has treated AI primarily as a reconfiguration of the work, monitoring, working conditions and governance of those who work in the HER sector. Reigeluth (this volume) develops the argument on evaluation, showing how automatised assessment and built-in standardised metrics are easy for a machine to produce, narrowing the social dimension of learning and teaching.

The analysis reveals interconnected dynamics: corporate partnerships create vendor dependencies and lock-in effects; such partnerships also transfer the control of education to private entities; datafication and surveillance erode privacy and autonomy; metrics-driven performance cultures intensify workloads and technostress; and governance frameworks remain fragmented, with decentralised policies that individualise responsibility rather than establish collective decision-making structures. This not only challenges the core of education but also its governance structures, which may conflict with its typical values of equity, academic integrity and academic freedom.

To counter these challenges, effective AI governance frameworks at European, national and institutional levels should be grounded in these rights and values. They should prioritise and invest in inclusive decision-making processes that actively involve HER workers in a democratic and transparent integration of AI systems and other data-driven technologies. Decentralised policies that shift responsibility should be replaced by coherent, accountable institutional governance.

This volume provides the research community, trade unions and regulators surrounding the HER sector with a critical assessment of the sociotechnical and legal dimensions of AI in the HER sector, as well as of the impact on working conditions and the potential for trade union action. The following chapters examine specific legal, technological and sociological issues. It also provides practical resources for legal interventions regarding the implementation of AI in the sector, supporting advocacy, trade union organising, negotiation, collective bargaining and resistance. Together, the contributions give a forward-looking call for governance to move in a direction that protects rights, integrity and professional and pedagogical autonomy.

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Abbreviations

AI	Artificial intelligence
AIEd	Artificial intelligence and education
EdTech	Educational technology (industry)
ETUI	European Trade Union Institute
EU	European Union
GenAI	Generative AI
HER	Higher education and research
OECD	Organisation for Economic Co-operation and Development
QAA	Quality Assurance Agency for Higher Education (a quality body in the UK's tertiary sector)
UK	United Kingdom
UNESCO	United Nations Educational, Scientific and Cultural Organization
VUB	Vrije Universiteit Brussel
XR	Umbrella term for virtual, augmented and mixed realities

Part 2
Sociotechnical perspectives

Chapter 2
Artificial intelligence and higher education and research: trends and trade union rights

Rob Copeland

Introduction

Debates on the use of artificial intelligence (AI) in higher education and research (HER) have tended to focus on the impact on student learning and assessment. There has been much less focus on the implications for staff in the sector, particularly on the working conditions and professional rights of researchers and academics (Crompton and Burke 2023; Tan et al. 2024). This chapter seeks to pull together some of the key issues for HER staff and the ways in which AI and digital platforms are interacting with the broader trends and challenges that the sector is facing. These trends include challenges to academic freedom and intellectual property rights, the fragmentation of academic roles and the casualisation of the profession, and commercialisation and privatisation in and of the HER sector. It also pulls together some examples of how trade unions at national and European levels are beginning to respond to these new challenges.

1. Academic freedom and intellectual property rights

Within the European Higher Education Area (EHEA), academic freedom designates the freedom of the academic community in respect of *research, teaching and learning* and, more broadly, the dissemination of research and teaching outcomes both within and outside the higher education sector (Bologna Process 2020). At national level, constitutional and legislative frameworks play a key role in safeguarding academic freedom across Europe. Academic freedom is also specified in a number of United Nations frameworks and is explicitly mentioned in the Charter of Fundamental Rights of the European Union (Art. 13).

However, over the past decade, there has been an erosion of academic freedom in many European countries (European Parliament 2023). During this period, political and ideological attacks on the freedom to teach and the freedom to research have increased. This has included attempts to target, monitor and discipline academics and students, most recently in response to Israel’s war on Gaza (SAR 2024). More subtly, academic freedom continues to be undermined by the commercialisation of higher education and research, in particular as a result of cuts in public investment, a greater use of private funding for research and a narrow focus by governments and employers on labour market outcomes (Iddeng et al. 2024). One of the consequences has been to limit the diversity of subjects, pedagogies and research perspectives in higher education.

These trends have coincided with the expansion of digital platforms in teaching and learning (Ponce Del Castillo and di Ridolfo, this volume). These platforms include specialist education systems, such as virtual learning environments and learning analytics software, as well as the products and services provided by 'Big Tech' (e.g. Microsoft 365). These platforms can affect academics' freedom to teach. In a report for Education International, Komljenovic and Williamson (2024) argue that AI-based digital products and services can run counter to principles of pedagogic freedom by supplanting pedagogic discretion in favour of platform algorithms. Similarly, as reported by Kissoon and Karran (2024: 13) 'employer-implemented forms of digital technologies are eroding academic freedom norms' in higher education in the United Kingdom (UK). These technologies – which can be found in many higher education systems across Europe – have facilitated real-time performance monitoring systems that allow academics to be 'compared' and 'ranked' across a range of academic tasks. Such systems allow employers to monitor the alignment of academics' research with 'institutional priorities' and on specific areas such as assigning 'income generation' as a key performance criterion (Kissoon and Karran 2024). While these developments are less serious than direct political and ideological attacks on individual academics, they do play a role in constraining individual freedoms to teach and research.

Intricately linked to academic freedom is the issue of the control and ownership of intellectual property. Already a complex area in higher education and research, digital platforms are further complicating questions of the academic ownership of research publications and teaching materials, including around their use and reuse. For example, in 2024, the publisher Taylor & Francis was widely criticised for selling thousands of papers to its Microsoft AI partner without the full knowledge of the original authors (Jack 2024). A number of countries have also seen disputes between trade unions and higher education employers over the control of online content and the video recording of lectures (Grove 2021). Although in its infancy, the advent of AI-based digital platforms is likely to exacerbate tensions over the control of intellectual property and staffs' personal and sensitive data and, therefore, will generate new challenges for higher education and research unions (Komljenovic, this volume).

2. Workforce issues: how AI intersects with changing job roles, contracts and workloads

As well as professional rights such as academic freedom, it is important to address how contractual and employment-related issues are affected by the expansion of AI-enabled technologies in higher education and research. In terms of key trends in the HER workforce, there has been an expansion of fixed-term and precarious contracts, the development of specialist teaching-focused positions (Wolf and Jenkins 2021) and the blurring of academic and professional services roles, including the rise of 'third space professionals' (OECD 2024). Some of the key drivers include the increase in student numbers, the growth of short-term and performance-based funding, the expansion of university missions and functions (for example, around widening access or knowledge exchange) and the growth of digital technologies.

In terms of digital technologies, when universities partner with EdTech platforms (Ponce Del Castillo and di Ridolfo, this volume), including with online programme management companies to provide core teaching functions, there can also be an impact on job roles and contracts for HER staff. Research into partnerships between such companies and universities, for example, suggests they rely on the academic labour of increasingly casualised, often outsourced workers. These groups of workers tend to be non-unionised, thereby raising important questions for traditional academic trade unions (Ivancheva and Courtois 2024).

Another key trend reported by education workforces and their trade unions is work intensification. This not only means an increase in working hours but also in the range and the complexity of academic tasks – for example, the need to prove that one's research has wider economic or societal 'impact'. The shift towards online, blended and hybrid teaching, which was given a huge boost by the Covid-19 pandemic, has been another factor in work intensification for both academic and professional services staff, particularly learning technologists and other IT-related specialists (Watermeyer et al. 2023a).

At the same time, it has been suggested that academics could reduce the workload burden by offloading some aspects of their work to AI, for example on course preparation and marking (Twabu and Nakene-Mginqi 2024). As the automation process in higher education gathers pace, it will be important to undertake rigorous research on the impact of AI-enabled technologies on the time allocated to different academic tasks. However, without a roll-back of commercialisation and privatisation (see below), generative AI tools may not lead to significant reductions in overall workloads (i.e. there will be pressure on academics to work harder on other tasks like generating new research funding bids). For example, a recent survey of UK-based academics found that 'the digitalisation of higher education through [generative AI] tools no more alleviates than extends the dysfunctions of neoliberal logic and deepens academia's malaise' (Watermeyer et al. 2023b: 446).

This suggests that union work on AI must go beyond workforce issues and seek to address broader political concerns around the changing nature and purposes of higher education and research. Central to this is the issue of commercialisation and the privatisation of higher education.

3. Commercialisation and the privatisation of higher education

Increasing commercialisation and the privatisation of higher education is a major challenge facing academic trade unions, a process which was accelerated during the Covid-19 pandemic (Williamson and Hogan 2020; Fleming 2021). In Europe, the main development over the past few decades has been 'endogenous privatisation' (Ball and Youdell 2008), whereby higher education institutions have adopted market-based funding and governance models. At the same time, there has also been a growth in 'exogenous' forms of privatisation, particularly the outsourcing of aspects of higher education provision to private providers (Ball and Youdell 2008).

Digital and online services have been a key driver of exogenous forms of privatisation. For example, during the pandemic, the shift to 'emergency remote teaching' and online learning positioned EdTech as a key element in higher education globally, bringing private sector and commercial organisations into universities as providers of core academic services (Williamson and Hogan 2021). Since then, the development of generative AI has led to further penetration by EdTech and Big Tech companies. As noted above, these developments are likely to have an impact on terms and conditions of employment, but in the longer-term they may also affect the wider mission and purpose of higher education institutions. As Williamson and Hogan (2021) argue:

> Rapid digital transformation of the sector driven by market valuations, the efforts of technology businesses to increase their market dominance in education, and the desires of investors for future cash flow, risks being profoundly undemocratic and [a] potentially damaging way to approach the future of higher education.

Through the intrusion of business interests as a driver of education development and the transformation of student data into a potential source of commercial value, the further expansion of EdTech risks undermining the public character of universities and, therefore, the notion of European higher education as a public good and a public responsibility (which is one of the fundamental values of EHEA). Consequently, in debates on the future of AI, trade unions must continue to assert the value of higher education as a public good and a human right – for example, by ensuring that AI-enabled technologies 'respect students' rights and privacy and avoid all kinds of discrimination and exclusion' (ETUCE 2024b: 9).

Conclusion: towards an education union agenda on AI

In light of these trends, it is important that unions start to engage in debates on digital platforms and AI services. Across Europe, higher education and research unions are beginning to examine the potential impact of AI on their members. For example, the University and College Union (UCU) in the UK has established an advisory group on the Future of Work in Post-16 Education to consider the threats and opportunities of the technology being used in the sector now and in the future, and how UCU should support members and branches to respond (UCU n.d.).

At European level, HER trade unions are increasingly working together to explore the impact of AI-enabled technologies on the academic profession (ETUCE 2023). Given the complexity and fast-moving nature of AI systems, it is important for trade unions to work with academic and legal experts to improve their AI literacy. A positive example of this can be found in the ETUI-ETUCE 2024 expert conference that gave rise to this volume (ETUCE 2024a).

Education trade unions must insist on a seat at the table when it comes to discussions about the use of AI in the workplace and in education. That will require meaningful social dialogue and collective bargaining at both national and European level, including ensuring that education unions have a role in the governance and oversight of AI-enabled technologies (ETUCE 2024b). Traditional union work must be complemented by advocacy and lobbying of the EU and Council of Europe around the development of appropriate regulatory frameworks that ensure AI systems in education are compatible with human rights.

Finally, education unions must work with the wider international labour movement to challenge the widespread physical, psychosocial and economic harms at work associated with the development and use of these technologies. For example, the experience of content moderators, who face low pay, surveillance, cognitive overload, trauma and other health issues associated with the relentless, unbroken, high-paced work tasks documented by the International Trade Union Confederation (2025), illustrates these broader risks. Trade unions have an opportunity not only to guide their members during the technological transition but to shape the introduction of AI in education by building specific expertise on AI, through cooperation with academic and legal experts, so that they can engage effectively in negotiations, governance structures and regulatory debates. This is essential if AI systems in education are to be introduced under conditions that respect academic freedom, safeguard working conditions and ensure compliance with fundamental rights.

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Abbreviations

AI	Artificial intelligence
ECFR	Charter of Fundamental Rights of the European Union
EdTech	Educational technology (industry)
EHEA	European Higher Education Area
ETUCE	European Trade Union Committee for Education
ETUI	European Trade Union Institute

HER Higher education and research
OECD Organisation for Economic Co-operation and Development
UCU University and College Union (UK)
UK United Kingdom

Chapter 3
Learning and teaching, or the limits of automating intelligence

Tyler Reigeluth

Introduction

In his classic 1964 text, Marshall McLuhan imagined a future in which learning would become the primary activity within heavily automated societies:

> The very same process of automation that causes a withdrawal of the present work force from industry causes learning itself to become the principal kind of production and consumption. Hence the folly of alarm about unemployment. Paid learning is already becoming both the dominant employment and the source of new wealth in our society. This is the new *role* for men in society, whereas the old mechanistic idea of 'jobs,' or fragmented tasks and specialist slots for 'workers,' becomes meaningless under automation. (McLuhan 1964: 351; emphasis in original)

This is a recurrent trope in theories of technological transformation: automation will free humans to do things that are 'really human' (i.e. be creative, learn, have fun and so on). Notwithstanding the more subtle aspects of McLuhan's theory of technology, what he probably could not foresee was that machines might end up automating learning itself. However, as Antonio Casilli (2025), among others, has pointed out, automation does not completely replace humans (e.g. Amazon has people executing the relatively simple, mechanical tasks of training intelligent algorithms), but it is redistributing the 'geography of intelligence' (Schaffer 1994) – where and what kind of activities, tasks and functions we deem intelligent are located in social and infrastructural space.

Calling something or someone intelligent is inevitably a social valuation, a form of judgement that necessarily implies there is something or someone else that is dumb, stupid, lazy or useless. We should therefore always be extremely careful when qualifying something as 'intelligent'. Artificial intelligence has come to stand for what is not human (Galanos 2018) but, to a large extent, human intelligence has always been artificial (think of all the tools we have used throughout human history: stones, paper, pens, abacuses, rulers, calculators, computers, etc.). Technology is a human product which shapes humans in return. How it shapes us and what we expect from it is a fundamental political question (Winner 1980). While we are far from grasping the extent and nature of the transformations we are living in recent years and months, there is at least one social institution which has long been specialised in shaping and transforming humans, and that is education.

The history of western philosophy has continually returned to the idea that education is the process by which a human being takes on a sort of second nature, a particular form within a given society. There have always been techniques involved in this process. One might even say that instituted education or schooling is an inherently artificial process wherein students are asked to perform certain tasks, with certain constraints of means and objectives. Previous technologies such as books, radio, television and the internet have disrupted teaching practices – although sometimes less dramatically than what was expected, promised or announced (Cuban 1986, 2018) – in the process always threatening to reduce or replace educators. However, this is perhaps the first time a technology, modelled after human learning, begs the question of what will be left for humans to learn or what kind of learning they will be doing. While it is doubtful these replacement scenarios are probable or helpful in any way, they do reveal something of what we have come to expect from teaching and learning in an age where 'intelligent' devices are popping up everywhere.

This contribution simply underlines two dimensions in the hope they provide some basis for debate: evaluation (i.e. how the deployment of artificial intelligence (AI) is affecting evaluation modes and objectives, but also how we evaluate AI's 'learning' and performance); and the relevance of the concept of 'technical culture' (Simondon 2012 [1958]) – that is, the kinds of practical and theoretical knowledge we can develop about the machines we use so that we are not merely users, in the context of AI systems.

1. Evaluation

As generative AI and large language models make it increasingly difficult to determine what part of work is done by humans or machines, one of the main challenges higher learning institutions face is the question of evaluation. And this question is at least twofold.

First, there is how we evaluate students in an age where not only endless information is readily available at our fingertips, but where systems can generate automatically paraphrased versions of published material, confounding questions of skill, plagiarism, personality, originality and effort (Kivinen, and Mäntysaari, both this volume). In short it raises the issue of what kind of virtues we aim at developing in students through their education. Again, this is not an entirely new question: books, calculators and computers transformed our relationship with memory, for example. But we seem still to cling to an idea of individual learning even though our education institutions have long been industrial in scale. Indeed, our evaluation systems tend to rely on performance metrics, tests and grading that are relatively easy for a machine to simulate. What this approach tends to miss is the inherently social dimension of learning and teaching – that is, what is being taught and learned – is not just free-floating content but reflective of social relations and values within determined activities (see the theories of Lev Vygotski).

When a human activity is reduced to a mechanical process, we are paving the way for machines doing it in our stead and evaluating performance based on that mechanisation (Collins 1990) (e.g. chatbots replacing client service relations that have already been reduced to scripted interactions). And this evaluation is not just about students but equally about educators: how are we evaluating educators when we are expecting them, for example, to draft multiple choice questionnaires that can be corrected by a machine? What kind of distribution of intelligence between students, educators and machines are we reproducing?

The second aspect of evaluation is how we evaluate machine learning itself. What kind of models of human learning are embedded in and reproduced by these systems (Reigeluth and Castelle 2021)? What is the standard we are using to evaluate the machines? By and large these models are heavily influenced by behaviourism, with vocabulary such as training, reinforcement or optimisation.

Machines are trained on data and expected to increase their score according to different metrics – engineers and computer scientists talk about optimising an objective function. There is a very narrow understanding of what learning and teaching means in AI communities; very little comes from social sciences or the humanities. And this seems to be feeding back into education practice more broadly. There is a 'technology' or engineering of learning (to a degree the behaviourist Burrhus Skinner could have only dreamed of) gaining ground within learning institutions with the likes of 'techno-pedagogical' personnel or units designed to assist and train educators in adopting new technologies, in streamlining, innovating, inverting their teaching. The reverse dynamic (i.e. the inclusion of sociologists, artists or philosophers in the design of machine learning algorithms or generative AI in a 'disruptive' way that potentially upsets or at least questions their underlying objectives and values) is still far from being normalised.

If we are to take the idea of machine *learning* seriously (i.e. learning as a social activity and not simply content transfer evaluated by standardised metrics), then it is time to begin considering what *machine education* might look like. Machine learning needs to be reclaimed as a cultural stake that is not limited to the reductive technical expertise and performance metrics of computer science engineers or data scientists.

2. Technical culture

Over fifty years ago, the French philosopher of technology Gilbert Simondon (2012 [1958]) underlined and worried about the growing distance that seemed to separate us from our technical artefacts and make us look at machines as if they were foreign to our culture. When we lack technical culture, we tend to adopt forms of magical thinking, irrational expectations or a fear of the increasingly complex and opaque technical systems that organise our daily lives. We tend to give technology more power than it actually has, imagining perfect automata that work without us, when in fact they break down, require care and maintenance and often generate unforeseen problems (Denis and Pontille 2025).

The technical culture Simondon called for was one that combined both theoretical knowledge and practical know-how – he famously asked his students to take apart and reassemble a motor for a final exam, emphasising that knowing a motor means thinking like a motor. Knowing how a car works, for example, involves notions of mechanics as well as having a feel for one's car (sensing its vibrations, noises, etc.); in other words, knowing how to drive it, which is not an entirely theoretical affair.

We can see how this kind of technical culture works for individual machines whose counterpart is an individual user. But what kind of technical culture do we need for AI systems which are multiscalar and distributed across disparate spaces? An individual system does not 'use' a network the way it uses an individual machine; it interacts with the network's symbols or interfaces. In the post-cybernetic age of networked technologies in which users increasingly interact with black box interfaces, the instrumental paradigm inherited from the Aristotelian tradition, according to which tools have no telos or values of their own, is cracking at the seams and revealing forms of engagement with technology that cannot be reduced to individual users learning how to use a tool 'correctly'. Indeed what constitutes the correct use of ChatGPT, for example, remains an open question that cannot be answered solely on a technical basis. Can we really say that AI's value depends on how we use it, when we are only interacting with a very thin layer of the technical ensemble's many dimensions? These are pressing questions especially considering that individual engineers recognise they cannot fully explain or account for these systems' behaviours.

In other words, there is no *one* specialist or expert among these systems, but complex assemblages of know-how and expertise. There is no one 'correct' or 'good' use, but multiple ends and values at play across multiscale networks. This can be seen as both a challenge and an opportunity for rethinking and reorganising the traditional disciplinary divides reproduced through higher education. Indeed, if higher education is to continue to be a place of critical thought that fosters democratic virtues, then its institutions must start preparing not just individuals, but collectives able to articulate different skills, experiences and forms of knowledge (Reigeluth 2020).

The answer to AI is not better skilled or trained individuals (i.e. masses of computer scientists who are 'properly' equipped to use these systems 'correctly'), but new forms of social organisation and institutions that can bind individuals together in collective action and knowledge. Being intelligent, whether it is said of a machine or a human, is always a reflection of the social division of the labour and infrastructures within which such intelligence is exercised – however 'intelligent' AI systems may be, they still require human labour and material infrastructures; these are their conditions of possibility, not disposable margins. Higher education institutions need not only educate specialists and experts in 'intelligent' systems, but form communities of practice and knowledge that have a legitimate claim to understanding how these systems work according to their perspective, their uses, their values and their disciplines. Technical culture in the age of AI will thus involve moving the subject of knowledge from the individual level (i.e. the skilled user) to that of the collective (i.e. the communities of practice). Higher education institutions certainly have a central role to play in this rescaling of knowledge.

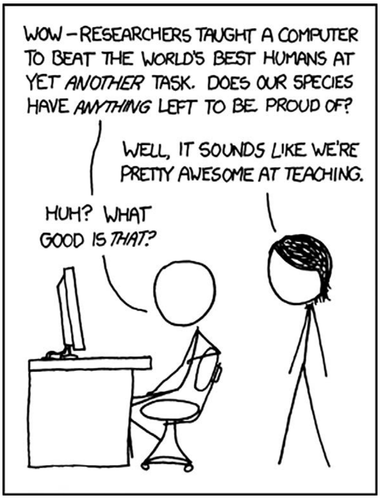
Conclusion

We value AI systems on the grounds that they allow unprecedented personalisation or participation; that they free educators from tedious tasks and allow them to focus on the heart of their profession. We fear them because they are seen as Trojan horses that make us do more with less; in other words, as another step in the tireless capitalist extraction of exchange value from living labour. But machines, especially 'learning machines', need not be only about automation, increasing output or optimising an objective function;

they can also be vectors for experimenting, learning, playful engagement, developing imagination and creativity. However, to paraphrase Kant, this indetermination supposes that the AI system should always be able to be taken as the end of learning and never simply as a means.[1] In other words, as users, learners and educators, we should have a fundamental right to game the algorithm (i.e. reappropriate the logics and the functioning of the systems we are simply supposed to 'use') (Bonini and Treré 2024). This ability of users to reappropriate the system involves questions of patents and intellectual property, but also of the procurement contracts institutions sign with service providers and platforms. This is essentially a question of technological pluralism or 'technodiversity', which is indissociable from diversity of thought ('noodiversity') (Stiegler 2020; Hui 2023). In other words, technical systems are never just tools at our disposal but also shapers of the ends we pursue, the skills we develop and the intelligences we (de)value and foster through certain activities.

In this light, 'users' should always have more than one way of doing things and accomplishing tasks; and thus always be more than simply users. Requiring everyone to use the same apps or platforms across diverse cultural, geographic and economic contexts is ultimately just a way of putting education to work even more. Teaching and learning exist within social and institutional fabrics and cannot simply be automated away precisely because there is never one single objective function to optimise, but multiple means of reaching multiple ends that must be weighed, debated, contested and evaluated (as Figure 3.1 humorously suggests):

Figure 3.1 **'Progeny', XKCD Comic 2011**



Source: https://www.explainxkcd.com/wiki/index.php/894:_Progeny
Licence: CC File:progeny.png - explain xkcd

1. Immanuel Kant's own rephrasing of his categorial imperative in the *Groundwork of the Metaphysics of Morals*: 'Act in such a way that you treat humanity, whether in your own person or in the person of any other, never merely as a means to an end, but always at the same time as an end.' (Kant 1993 [1785]: 36)

It is worth remembering that Luddites did not break machines simply because they refused machines as such, but because they did not want their work done *like that,* in *those conditions* (Thompson 1991). Higher education institutions still have the power and the means to take part in shaping the 'like that' – the conditions of our work as educators, evaluators and learners. However, reclaiming that power will involve developing technological infrastructures, skills and collective practices that are not dependent – as increasingly is the case – on oligopolistic platforms; that is, *exercising our intelligence* as institutions of learning and teaching.

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Chapter 4
Behind the algorithms: the implications in higher education

Pedro Oliveira

Introduction

Algorithms in higher education must be seen in the broader context of the digitalisation of education. But what does digitalisation mean in an education context? It can denote the use and integration of digital technologies in classroom settings (teaching and learning materials) or the wider concept of a digital school, which also encompasses the use of information technologies in administrative tasks such as student attendance, grade publication and summaries, among other things. The pandemic-induced shift to remote learning has undeniably accelerated digitalisation, a shift that would not have occurred were it not for the emergency prompted by education institutions being closed to minimise Covid-19's effects on learning.

The paper is organised as follows. In Section 1, the pervasive use of digital technologies and the implications for an active and engaged citizenship are briefly presented. In Section 2, the impact of the digitalisation of education is discussed on two fundamental dimensions for educators: how it may change the pedagogical approach to teaching; and, consequently, how the required learning and use of these technologies will change the profession. Section 3 debates the repercussions of digitalisation in higher education before, lastly, the conclusion is presented.

1. Digital citizenship

A digitalised society raises critical questions about citizenship and societal participation amidst its increasing demands on digital literacy, for example: filling out forms, prescriptions, exams and tax declarations; applying digital signatures; and searching the internet for information and using social networks. All these activities require new skills in information technology, communications and information retrieval (Dijck et al. 2025).

Active and engaged citizenship in a democratic society, immersed in an increasingly digitalised world, requires that teaching institutions play a crucial role in building digital citizenship, especially for younger generations. Active citizenship may, however, be compromised by inequalities in access to the internet and devices for students and families – inequalities that have often long been invisible, but not only became more apparent but were also even exacerbated during the pandemic – and by the concept of remote learning (Keegan 1980; Hamilton and Feenberg 2005; Goodfellow 2006; Golden et al. 2023).

The Covid-19 pandemic also heightened educators' awareness regarding the transformative impact of digitalisation on teaching and learning methodologies, with a significant impact on the lives of students and educators, prompting a re-evaluation of pedagogical and professional approaches to education in the digital age (Ponce Del Castillo and di Ridolfo, this volume).

2. Pedagogical and professional impact

Discussions about the digitalisation of education (Gariel 2021), which incorporates the use of artificial intelligence (AI) (such as machine learning, neural networks and generative AI), should consider two dimensions: the pedagogical and the professional.

From a pedagogical perspective, assuming there is a consensus on digital literacy for full citizenship – and bearing in mind here the desire of the European Union (EU) to establish a 'shared vision' on digital competencies (Vuorikari et al. 2022)[1] – the questions raised by digitalisation include:

— how is knowledge acquired?
— how should the massive amount of information to which we are privy be managed?
— how is critical thinking developed?

First, it is paramount to distinguish between information and knowledge; the latter emerges from the interactive process of teaching and learning, driven by the fundamental human bond between educator and learner. Reducing education to a simple assimilation of readily available information on the internet denies the mediating role of the educator as an essential element in the process, one who is capable of understanding individual student needs and strengths and creating an inclusive and quality educational process.

Second, how should the massive amount of information and sometimes truth-lacking content (in the sense of malicious, intentionally deceiving misinformation or otherwise harmful information) be dealt with in the digital world? The deluge of digital information poses challenges to critical thinking and knowledge acquisition (Gariel 2021), emphasising the role of educators in demanding and conveying truth, especially when information is sourced from the internet and social networks controlled by algorithms that may limit perspectives. Such algorithms are tools developed by humans, in which process they impart their own preconceived ideas. For example, AI tools like DALL-E, a text-to-image model developed by OpenAI, produced biased images when prompted to display figures of lazy students (mostly female) or hard-working ones (mostly male), or homeless (mostly ethnically diverse people), or architects (mostly male) (Bianchi et al. 2023). At the same time, these tools can provide reshaped images of famous paintings, write essays and rewrite texts from original sources all without acknowledging authorship.

1. In the field of what students should be required to know, for instance, such competencies include: how to use word processors and spreadsheets; how to create digital presentations; how to use open source software, social networks and AI tools; and awareness of the privacy risks encompassed by digitalisation.

This is especially worrying since students 'might unknowingly and without critical engagement accept generative AI output that is superficial, inaccurate or even harmful' (UNESCO 2023a). Therefore, the capacity to develop critical thinking (the competence to evaluate, understand and be critical of material retrieved from the internet or other sources) is paramount.

Professionally, the shift towards digitalisation, and the pedagogical implications that result from its introduction in the process of teaching and learning, raises relevant questions:

— what changes does it bring to the profession?
— to what extent does digitalisation change pedagogical thinking?
— to what level should education include new digital knowledge?

Many educators are not fully acquainted with the use of digital tools (like software, online digital platforms or generative AI) in their teaching. According to an Organisation for Economic Co-operation and Development (OECD) survey (OECD 2020), '65% of 15-year-olds are enrolled in schools whose principal considers that teachers have the necessary technical and pedagogical skills to integrate digital devices in instruction'; however, this percentage varies widely across countries and, within a country, among education institutions, particularly between advantaged and disadvantaged ones. Furthermore, a United Nations Educational, Scientific and Cultural Organization (UNESCO) survey among 450 schools and universities regarding the ethical and pedagogical implications of these digital technologies found that 'fewer than 10% had institutionalised policies and guidance concerning the use of AI applications' (UNESCO 2023b). As a result, educators need to learn the use of these tools (Vincent-Lancrin and van der Vlies 2020) and, therefore, professional training is required. In general, educators acquire knowledge in this area mostly by sharing information with colleagues or through watching videos or reading articles. Consequently, the profession is already changing as a result of the introduction of digital tools.

The digitalisation of bureaucratic processes (such as, for instance, control of attendance, summaries, grade registering, biographical data of students (age, ethnicity, gender, social origin, grades), information exchange between educators and students or exam and lesson timetabling), along with the time constraints imposed by filling out information forms, is placing educators under greater pressure, increasing their workload. This contradicts the supposed efficiency that digitalisation brings to such processes; for example, the more processes are digitalised in order to reduce the time they require individually, the more time is required to respond since more specific tasks are being added. Moreover, the digitalisation of education, with the expectation that educators be available at all times (such as through the use of e-mail at any time of the day), changes working conditions regarding work-life balance, in particular the right to disconnect.

Frequently, the question is not just about learning how to use a tool but strategically thinking about its use for pedagogical purposes. Educators need to develop information literacy skills, for example the ability to seek, evaluate, select, process, understand

and use information (Gariel 2021); thus, they need to develop research, computer and communications skills as well as a critical perspective on the use of these technologies, their benefits and risks so they are equipped to teach this crucial skillset. The integration of digital tools thus implies a shift in pedagogical thinking.

Although digital tools may reduce the workload of educators, in order to master them, they first have to learn how to use them. Thus, they 'will have to adapt their pedagogical approaches to work with automated technologies' (Williamson 2023). Specifically, this pertains to how these tools are employed in the classroom setting – most obviously in terms of the student-educator interactions mediated by digital technologies, lesson planning, the development of pedagogical materials tailored to the specific tools used, and the processes of assessment and feedback provided to students. As stated by Williamson (2023) the risk is that AI could robotize the role of the human teacher, in that the educator is commanded by these tools (what course syllabus to follow, what to teach, when and how to do it).

In this sense, the use of AI must be human-centred and its use in education should be the result of pedagogical debate, taking into consideration its long-term implications, namely on bias and discrimination, data privacy and the psychological impact on students and cultural diversity. Awareness that the majority of these tools are produced in Silicon Valley, reflecting the views and cultural values of their developers and, somehow, blinded to the diversity of human populations, is essential (Miao and Holmes 2023).

Third, the digital presence in almost all aspects of social life raises questions about the necessary life skills for an active digital citizenship. This is recognised by the European Commission, which has published an action plan (European Commission 2020) mostly centred on the political importance and challenges that digital skills and competences pose to European education. This in turn led it to publish a digital competence framework with the aim of 'creat[ing] an agreed vision of what is needed in terms of competences to overcome the challenges that arise from digitalisation in almost all aspects of modern lives' (Vuorikari et al. 2022: 4). Ultimately it is the role of education institutions to define the curricula, which means they need to define the skills and competences that students should develop along their diverse academic life. What should be taught, at what age or level of education, is a discussion that society at large, and education institutions themselves, have not engaged in with sufficient reflection. Thus, the diversity of European nations requires that their education systems define what digital skills are needed so that a common denominator is set for the European Union.

Moreover, the introduction of these technologies raises issues regarding academic freedom and intellectual property of the works produced by educators (who owns the pedagogical materials they produce: educators themselves or the institutions where they work? Who defines what to teach or what to research?). Furthermore, new ethical problems are emerging, substantially concerning the use of individual data (student grades, for instance) by private software, as well as decision-making (hiring and job selection) being made by algorithms that are opaque to users (ETUCE 2021; Miao and Holmes 2023).

3. What questions does AI raise in higher education and research?

It should be understood that AI algorithms can be biased since they are based on historical and training data that may, by themselves, be biased. Moreover, AI tools are developed by humans who have their own biases which are projected, consciously or unconsciously, on those algorithms. There are many examples of where outcomes are biased in terms of gender or race, for example. Larson et al. (2016) exhaustively analysed the COMPAS (Correctional Offender Management Profiling for Alternative Sanctions) tool developed by Northpointe, used in the United States by judges and probation officers for reviewing parole applications, and 'found that black defendants were far more likely than white defendants to be incorrectly judged to be at a higher risk of recidivism, while white defendants were more likely than black defendants to be incorrectly flagged as low risk' (Larson et al. 2016). This work also highlighted that the human decision-makers at the end of the algorithm may not correct the bias. Therefore, having a human at this point is not a guarantee of a lack of bias and, moreover, in detecting bias it is necessary to have a large amount of data concerning decisions. If bias is found, even if it is corrected, its harm has already been done. Hence, ethical questions can also be raised in the use of AI tools for grading and admissions to universities or for job selection.

It is important to highlight in addition that the environmental impact of the energy consumption and cooling requirements for data centres is significant, with projections indicating a fourfold increase by the end of the decade (Harvey 2025), although the issue has received only limited attention (Brevini 2020; Mendes 2024). Furthermore, the often-overlooked phenomenon of hidden and exploitative (slave) digital labour is frequently regarded as insignificant or too discrete to be acknowledged (Perrigo 2023; Casilli 2025). This contributes to the 'illusion of automation' while simultaneously hindering economic dignity, job security and better working conditions (Casilli 2025).

Differences in access to the internet or digital technology, as experienced during the pandemic in taking advantage of remote learning, and also due to differences between institutions, may create a digital divide between students in differently affluent institutions (some universities are giving their students access to the paid version of ChatGPT).

In the context of the use of digital tools in teaching, the student is placed in front of a computer screen and presented with the possibility of interacting with all the other tools available and, thus, may be distracted and less attentive and, therefore, less focused on learning. Several studies (Galanos 2023; Simon et al. 2023; Treetop ABA Therapy 2024; Samba Recovery 2025) report that the average attention span has decreased during the last two decades (to around eight seconds in adults), mostly caused by the environment around the internet and social networks. This has a strong impact on young adults whose relationships and social structures are highly online dependent and who, in the context of the lecture hall, will be exposed to distractions from active work. For these reasons, the integration of digital tools will entail a change in pedagogical thinking and approach since the lack of human connection may induce students to feel alienated and less engaged in the learning process. Most algorithms are based on a standardisation of what is perceived as the proper way to learn and may disregard differences between students and their individual needs and strengths, and thus, potentially, aggravate inequalities.

Plagiarism is the most immediate fear, together with the possibility of wrong answers. Policing is impossible since students may access AI tools from other devices (such as mobile phones or tablets) or at home, further deepening the digital divide since the more wealthy students will have access to paid and private accounts; it will also create a confrontational relationship with students and consume educators' time which should, otherwise, be directed to teaching and promoting debate with students.

The main challenge, however, is how to transform the use of AI to enhance pedagogical outcomes and critical thinking. AI has much potential, for instance in generating coherent texts and processing natural language (interpretation of complex texts, creating essays and generating images or slides). Consequently, the focus should be on teaching students to use generative AI critically, as a support tool, and not simply to copy and paste the information that appears. In this respect, Google and Wikipedia are also at students' disposal; however, there is a difference since users must review and then choose which links to use whereas in generative AI they receive a response which they may or may not then question further.

As stated by Rayner (2004), 'ambitious claims for revolutionary innovation' may be confronted 'with concerns about unintended consequences and new risks'. For instance, the basing of assessments on essays may no longer be pedagogically useful. Therefore, educators have to envisage new ways of assessment and innovative ways of using these tools with a pedagogical purpose focused, importantly, on the development of critical thinking.

Conclusion

Today's students will graduate in a digitalised world with a diversity of digital tools such as generative AI. Therefore, full and active citizenship requires that students need to know and be aware of AI tools to understand how they work, the ethical questions they raise and how they can be misused and weaponised. This consciousness of the impact of digitalisation, present in almost all realms of life, not only demands that education institutions (secondary or higher) take the necessary actions to prepare and teach students for digital citizenship, but also requires that educators learn how to navigate this digitalised sea. Therefore, innovative approaches to pedagogy are required in connection with educator and student interaction and, above all, as a result of the need to develop critical thinking.

Thus, educators and their unions have to be fully aware that digitalisation will change the profession especially as regards its impact on pedagogy. A critical approach to digitalisation in education can only emerge through the involvement of educators, students and other stakeholders (staff, parents, politicians, trade unionists, AI vendors and other members of society with an interest in this process), in a form of societal technology assessment (Rayner 2004). It is imperative to navigate this transition with a keen awareness of both the opportunities and the challenges it presents. In this task, education must be recognised as a fundamental pillar in the construction of a more democratic, just, inclusive and egalitarian society. This challenges educators, institutions and society at large to prepare citizens for the proper use of these AI tools.

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Abbreviations

AI	Artificial intelligence
COMPAS	Correctional Offender Management Profiling for Alternative Sanctions
ETUCE	European Trade Union Committee for Education
EU	European Union
OECD	Organisation for Economic Co-operation and Development
UNESCO	United Nations Educational, Scientific and Cultural Organization

Part 3
Legal considerations

Chapter 5
Extended reality technologies in higher education: five threats to privacy and data protection

Elora Fernandes

Introduction

Online virtual worlds peaked in popularity within higher education institutions in 2007. The platform Second Life was particularly popular, with universities leasing 'islands' where students and faculty staff could interact through avatars in immersive virtual campuses. At the time, these digital spaces were mainly used for lectures and could be integrated with other technologies such as learning management systems. However, despite the buzz and high hopes, they did not gain much traction. Limited creative use beyond lectures, the need for powerful hardware and fast internet access — which many students and education institutions lacked — together with issues like abusive behaviour and accessibility challenges, quickly undermined the momentary hype (Weller 2020).

Around the mid to late 2010s, however, extended reality (XR) technologies became more accessible and affordable, thus being increasingly used for educational purposes. XR can be understood as an umbrella term encompassing different ways to experience reality such as augmented reality (AR), virtual reality (VR) and mixed reality.[1] While the application of XR in education remains under-researched, preliminary evidence suggests it holds promise in three key areas (Cortesi et al. 2021: 9-10). First, it can enhance skill-based learning, particularly in foreign language acquisition as immersion has shown to be beneficial. Second, it could significantly expand the range of hands-on learning experiences available to students, such as virtual journeys inside the human body. Third, it introduces functionalities and opportunities for learners to engage with knowledge in ways not previously possible, for example by simulating architectural designs in class.

These potential benefits are yet to be fully realised and are often accompanied by excessive expectations and unwarranted optimism. Furthermore, XR technologies pose significant risks to the rights to privacy and the protection of personal data. Although these are mostly the usual suspects related to the processing of personal data, especially when artificial intelligence (AI) is involved, the inherent functionalities of XR technologies may give rise to them in new ways (Berrick and Spivack 2022). This demands a more careful balancing of the opportunities and the risks given the fundamental rights that are at stake.

1. There is no clear consensus, either in the academic literature or in industry, on the exact definitions of any of these terms. Rauschnabel et al. (2022) extensively map the different ways of conceptualising them and highlight how the boundaries between these concepts are not well defined. The authors address this gap not only by organising the debate but also proposing a new, more coherent framework around the idea of 'xR' (the lower case 'x' representing a placeholder for any digital reality format).

After this introduction, Section 1 highlights five key challenges that must be addressed before integrating XR technologies into education: the type and volume of data processed; real-time data collection; data repurposing; bystander privacy; and the collection of data in (semi-)public spaces. Section 2 then briefly touches upon how the current European Union (EU) legal framework deals with these challenges, especially the General Data Protection Regulation (GDPR) and the Artificial Intelligence Act (AI Act) (Ponce Del Castillo, this volume). Finally, it concludes by summarising the key insights and discussing the paths forward.

1. Five risks to privacy and data protection

1.1 Types and volume of data processed

The aim of XR technologies is to provide a seamless integration of the physical and virtual worlds, in different degrees. Especially when it comes to immersive XR, the processing of data needs to occur at the micro level; that is, through the granular and often continuous processing of personal data. Although the risks associated with processing large amounts of data, particularly sensitive data, are already present in the digital environment as a whole, XR technologies facilitate and enhance data collection. This allows for long-term and detailed tracking of information on a scale previously unattainable (Abraham et al. 2020).

When it comes to VR headsets, for instance, the collected data would include at least those related to head position and movement tracking (needed to calibrate the hardware and prevent motion sickness); eye movement captured by internal cameras (allowing users to interact with content based on where their gaze is directed and to simulate eye contact with other users); and spatial maps of users' physical surroundings (Olaizola Rosenblat 2023). However, the types of collected data can, and often will, extend beyond these essentials. They may include other physical body movements and patterns (such as from the hands), biometric data[2] (such as face prints, voice patterns, iris scans and physiological indicators like blood pressure), neural activity (Li et al. 2023) and data from the user's physical environment (such as sounds, location and visuals). A typical consumer-grade XR system collects points of interest of the human body between 60 and 144 times per second (Nair et al. 2023) which could result in the collection of millions of data points from just a few minutes of usage (Pahi and Schroeder 2023). Furthermore, these are also often then blended into datasets obtained from third parties.

The sheer volume of data is accompanied by them being of a specific quality, many being considered biometric, or sensitive more broadly. One important example is motion-tracking telemetry data, which lie at the core of XR experiences and are related to 'the position and orientation of tracked locations on the user's body in the 3D space' (Nair et al. 2023). The way people move around forms a strong component of their expression as human beings. These movements are shaped by each individual's unique physiology,

2. See Galea: the world's most advanced biosensing headset that collects biometric data, produced by OpenBCI.com. https://openbci.com/content/galea-brochure.pdf

muscle memory and personality, meaning that motion data could even be considered biometric — data that can uniquely identify individuals (Nair et al. 2023b).[3]

Motion data, together with the other kinds of data collected by eye-tracking technologies (for instance, Soares et al. 2023), emotion recognition technologies or brain-computer interfaces, could lead to the creation of 'biometric psychography' profiles (Heller 2020). This breadth and sensibility of data enhances the ability to infer information detailing individuals' interests, aversions and vulnerabilities based on their involuntary and often unconscious reactions to the world's stimuli (Olaizola Rosenblat 2023).

The unprecedented scale of data processing makes it highly unlikely for data subjects to be aware of the type and volume of data being collected, as well as the timing and purposes of their collection (Abraham 2022). The immersive nature of some XR technologies adds another layer of complexity to privacy management. Users may find it challenging to grasp and manage their privacy preferences effectively. Moreover, this large amount of collected data, if leaked or accessed by unauthorised parties, has the potential for far-reaching consequences.

Apart from vast data collection being an issue for data control in itself, a related challenge is linked to the automated decisions that can be made about students and educators, enhancing the chances of bias, unfair profiling and the crystallisation of previous situations. Examples include determining a user's economic status through the type of hardware they're using or based on their engagement in a virtual or augmented reality shopping experience. Another is drawing relational or networking inferences, such as the social groups a user is or is likely to be part of, determined by factors like preferred XR software, ethnic, cultural or religious background, political affiliation, etc. (Pahi and Schroeder 2023).

1.2 Real-time collection of data

The real-time and continuous collection of data is extremely important for the sense of presence and the embodiment of individuals in virtual worlds. While this enables unparalleled granularity in understanding user behaviour, psychology and actions, it also poses significant challenges to data protection. The constant flow of data makes it difficult to adhere to principles such as purpose limitation and data minimisation. Users' actions and interactions are often unpredictable, making it challenging for data controllers to anticipate what they will actually collect and to maintain prior transparency with users. It also enables or reinforces real-time manipulation, nudging and abuse (McGill 2021).

Humans have evolved to trust our senses. This renders the notion that the perceived environment could be entirely fabricated something for which we are not mentally

3. Nair and colleagues (2023a) analysed data captured from 55,000 users of a game called Beat Saber, using 2.5 million motion capture recordings. Their goal was to determine whether training machine learning models on the recordings of each user could enable the identification of individuals based on their motions in different in-game maps and on different days. Their results demonstrated that a user can be uniquely identified with 73.20% accuracy using just 10 seconds of data, and with 94.33% accuracy using 100 seconds of data.

prepared. Therefore, immersive media exerts a profound influence on our perceptual channels, which becomes even more powerful when profiling is used to adapt the virtual environment (Cairns 2023; Krauss 2024; Spivack 2024). A study conducted by Breves (2021) indicated that individuals who felt a strong sense of spatial presence rated the content presented to them more favourably because they relied on heuristic processing. As a result, their positive evaluations led to biased systematic processing, which made the content persuasive even if the arguments were weak. When employed in an exploitative way, it has the potential to become the most powerful tool for persuasion and manipulation ever created (Rosemberg 2022), through the integration of real-time surveillance with real-time influence (Olaizola Rosenblat 2023).

1.3 Repurposing data collected though XR technologies

A significant risk in XR environments stems from the repurposing of data — that is, using data collected for one initial purpose (e.g. education or interaction in virtual environments) for secondary ones. Information gathered in an education setting can inform decisions across a wide range of areas and can be considered valuable for different stakeholders such as companies, data brokers, social scientists, political parties and governments (UNESCO 2022). The collection of data related to user behaviour and health could, for example, be used to influence health insurance premiums. Neurological data related to students' attention levels could be part of an assessment of mental illness or academic performance. Employers could use data on cognitive load or performance under stress as a pre-employment screening tool.

Beyond posing challenges to principles such as purpose limitation and data minimisation, the presence of incentives — particularly commercial ones — for collecting data beyond what is strictly necessary means that relationships in education are increasingly being structured around data production, often with an eye toward reuse, and shaped by private actors' interests.[4]

1.4 Bystander privacy

The issue of bystanders adds a fourth layer of complexity to the data landscape of XR technologies. Even individuals not actively engaging with these technologies may find their data being processed when others in their environment are doing so. While most of the privacy and data protection issues affecting bystanders will mirror the ones faced by XR users, the former are even more likely to be unaware of any data processing activity involving them (Berrick and Spivack 2022). This creates unique challenges that go beyond data protection requirements such as transparency, lawful bases or data subject rights: it necessarily involves discussions related to the level of interference in privacy that society is prepared to tolerate.

The privacy and data protection of bystanders are particularly at risk when AR technologies are employed. Unlike VR, body-worn cameras and other wearable devices,

4. See Principle 6 of the Danish Regeringens Ekspertgruppe Tech-Giganter (2024) report on the role of Big Tech in digital infrastructure.

the capabilities of AR fundamentally rely on sensing environmental data to function (O'Hagan et al. 2023). This not only amplifies the existing concerns but also introduces new risks including the possibility of being identified by the user of the technology (and also by its developer) and of being profiled, as well as the challenge presented to anonymity in (semi-)public spaces.

AR technologies also enable users to alter physical reality, providing them with augmented perception such as *superhearing* or *supersight* that could be used for personal surveillance. These enhanced capabilities could be used to alter the way people are perceived by AR technology users; that is, by their digital self-representation. Bystanders' images could also be misappropriated for identity hacking or for creating deepfake content that sexualises an individual or misrepresents their identity (O'Hagan et al. 2023).

1.5 Collection of data in public or semi-public spaces

Related to the issues concerning bystanders, the deployment of XR technologies in public or semi-public spaces such as education institutions, hospitals, museums and parks presents critical privacy risks that extend beyond current data protection laws. In these settings, physical presence alone can subject individuals to data collection, often without their knowledge or consent.

The nature of these technologies creates ambient surveillance, an always-on data collection process that blurs the line between personal and public space. This may significantly undermine expectations of privacy while it may also have a direct impact on other fundamental rights such as freedom of expression or assembly. The chilling effect on discourse, wherein individuals self-censor their behaviour (Hine et al. 2024; Hine, this volume), can also directly affect the right to education and pedagogical autonomy as learners and educators may feel constrained, less willing to express unconventional or critical ideas, or reluctant to engage in learning activities for fear of being monitored.

2. Legal framework

As these risks to data protection show, XR technologies in the education environment create several challenges in terms of compliance with the GDPR. The real-time trove of data collected — often including special categories of information gathered from vulnerable individuals such as young students and workers — combined with the immersive nature of these technologies, pose significant risks for both users and bystanders if not strictly limited and processed lawfully. XR technologies also entail complex data flows, involving multiple layers of processing and numerous actors, particularly when AI systems are integrated and a broader value chain engaged.

In this sense, purpose limitation, data minimisation, data security and data protection by design are key principles that must be upheld in order to deal with some of these challenges. This calls for a needs-based approach. Tools should only be adopted if they are *necessary* to achieve a clearly defined pedagogical goal (and data processing purpose) — supported by scientific evidence[5] — and where no less invasive alternative can achieve the same outcome. In addition, the *proportionality* of this implementation should be assessed, balancing the *proven* benefits to certain rights, such as education, against the risks to others, such as data protection.

The challenges related to bystanders and the use of XR technologies in (semi-)public spaces are a bit trickier to deal with. This is especially relevant in a future scenario in which these systems might become ubiquitous and interconnected, as they could be exploited by private companies and governments, potentially threatening the essence of the fundamental rights to privacy and data protection (González Fuster 2022). Dealing with these challenges necessarily demands that democratic discussions define acceptable levels of interference with privacy in public spaces (by private and public actors) and establish clear legal standards for reasonable expectations of privacy. This also means advancing the technology to provide better support by design for explicit and implicit approaches to distinguishing between those who are active users of XR technologies and those who are bystanders.[6]

All these issues are even more complicated when AI systems are in place. AI specificities have long been creating tensions with GDPR. For instance, although inferred data is also considered personal data and under the scope of GDPR, and individuals have the right to explanation when automated decisions are made about them,[7] there is still a gap in the legislation related to how inferences are drawn (related to problems of subjectivity and verifiability: Wachter and Mittelstadt 2019). There is also an issue when AI models developed for one purpose are used in other contexts, even when the training dataset is anonymised (Häuselmann and Custers 2024).

The AI Act does not solve these specific uses, though it remains an important development especially in banning some specific technologies that pose unacceptable risks to fundamental rights. Its Art. 5 includes prohibitions on practices that have a significant potential to manipulate people through subliminal techniques beyond their consciousness; those which exploit the vulnerabilities of specific groups, including due to age, disability or specific social or economic situation; and those which infer sensitive data through biometric categorisation. More specifically related to education, Art. 5(1)(f) prohibits the use of AI systems to infer emotions in education institutions, other than for medical or safety reasons (Ponce Del Castillo, this volume).

5. Concerning the implementation of XR in learning, and of educational technology (EdTech) more broadly, robust, independent scientific research on a significant scale is still scarce (Holmes 2023; Kucirkova et al. 2023).

6. Explicit approaches require more active participation from the bystander to make differentiation possible, such as performing a gesture, using a specific item or directly opting out of the system. Implicit approaches, on the other hand, rely on other aspects like distance from the camera, eye gaze direction, position in the frame, etc. Although the latter is often preferable, since it can protect people who are unaware of the technology, there are still risks related to poor performance when bystanders behave in ways not previously expected. Additionally, these systems are often implemented off-device, requiring bystander data to be transferred elsewhere (Corbett et al. 2023).

7. Court of Justice of the European Union (judgement of 27 February 2025) in the case of *CK v Dun & Bradstreet Austria* (Case C-203/22).

Education and vocational training is also a category for AI systems to be potentially classed as high-risk (Art. 6(2), Annex III), meaning that several specific obligations must be followed by providers and deployers. This encompasses AI systems intended to be used for determining the access or admission of students to education institutions; evaluating learning outcomes; assessing the appropriate level of education; and detecting any prohibited behaviour of students during exams. Another significant category pertains to employment, worker management and access to self-employment, including AI systems used for recruitment and making certain decisions within the work environment. Enhanced transparency requirements (Art. 50) may also apply when generative AI is used in XR technologies.

Although a step forward, the AI Act also has many caveats. Apart from not solving some of the clashes between GDPR and AI technologies mentioned above, there are several exceptions to be considered when applying some of its provisions. These include Art. 6(3) which allows providers to decide, based on specific criteria, when the AI system does not pose a significant risk of harm to health, safety or fundamental rights and which, therefore, should not be considered high-risk; or the broad possibility of using emotion recognition technologies for medical and safety purposes. Risk is, in general, also self-assessed by those to whom the legislation applies, meaning that it may raise concerns related to legitimacy and give rise to conflicts of interests in practice. It also remains to be seen how the AI Act will reconcile, in practice, the risk-based approach within product safety legislation with the need properly to consider values such as human rights, democracy and the rule of law.

Conclusion

XR technologies hold significant potential in education, enabling students and educators to interact with reality and knowledge in innovative ways. However, their operation relies on the real-time collection of vast amounts of data, particularly special categories of data in order to integrate the physical and digital worlds seamlessly. This raise several challenges briefly discussed in this chapter, including not only the volume and type of data processed, but also data repurposing and the collection of data from bystanders, especially in (semi-)public spaces.

GDPR and the AI Act contain important requirements that, if effectively implemented, would help address some of these concerns. These encompass, especially, purpose limitation, data minimisation and an assessment of necessity and proportionality.

More than merely complying with the legal framework, however, the application of XR in education must be embedded in a broader democratic education strategy that actively involves educators, students and their representatives. The history of EdTech demonstrates that the cult of innovation for its own sake is often detached from its political and societal implications (Fernandes 2024). Though the specificities of certain technologies, such as XR, certainly warrants discussion, the focus should also be on integrating them as part of a holistic approach to achieving key educational goals such as equity, inclusion, and educational quality.

Moreover, as the influence of private actors in educational technology grows, it is essential to rethink the public-private power dynamic to ensure that public interests take precedence over commercial imperatives. This requires discussing digital sovereignty in strategic sectors such as education, including what kind of technology aligns with educational values and with those responsible for developing them, and drawing up specific rules in public procurement processes that could safeguard democratic oversight, prevent vendor lock-ins and proactively address the risks related to privacy and data protection before they materialise.

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Abbreviations

AI	Artificial intelligence
AR	Augmented reality
EdTech	Educational technology (industry)
EU	European Union
GDPR	General Data Protection Regulation
UNESCO	United Nations Educational, Scientific and Cultural Organization
VR	Virtual reality
XR	Extended reality

Chapter 6
Implementing the AI Act in higher education and research: compliance tools and worker participation

Aída Ponce Del Castillo

Introduction

Data-driven technologies are structural elements of the education system, with generative AI (GenAI) emerging as a significant driver. Higher education and research (HER) institutions are well positioned in deploying and integrating them and, as this process accelerates, regulating AI will require a sector specific approach. Ministries of education, education institutions and technology providers will be required to assume greater responsibility and to demonstrate transparency in the selection, implementation and justification for the AI systems used in the education sector.

Recital 56 of the AI Act passed by the European Union (EU) recognises the importance of technology in education and the need 'to promote high-quality digital education and training and to allow all learners and teachers to acquire and share the necessary digital skills and competences, including media literacy, and critical thinking, to take an active part in the economy, society, and in democratic processes'.

However, the Act follows the New Legislative Framework model for EU product regulation, combining essential legislative requirements with harmonised standards, quality management systems and market surveillance. It does not explicitly address the nuances of data processing and technology use in education, including HER; it simply regulates how AI systems are put on the market or into service in the EU. Although it acknowledges bias in AI systems, it lacks specific provisions to address the particular needs of disabled students and disabled educators, and of people of certain racial or ethnic origins or sexual orientation (Recital 56). It also does not directly tackle potential issues like financial inequalities in accessing these systems, internet dependency or vendor lock-ins. This raises questions about the Act's effectiveness in the governance of data-driven technologies within education.

Dependencies are also not addressed by the AI Act. Where EdTech platforms and AI systems rely on gatekeeper core platform services, the Digital Markets Act becomes relevant as a horizontal lever to reduce gatekeeper-driven lock-in and widen real procurement choices. Where HER environments are mediated by very large online platforms or very large online search engines, the Digital Services Act is relevant as an instrument for transparency and systemic-risk governance.

This chapter operationalises the AI Act in the HER context, translating complex legal provisions into sector-specific guidance. It offers a sector-specific, rights-focused regulatory analysis of the Act, identifying where the horizontal provisions fall short of sector-specific needs, noting that these are expected to be supplemented by harmonised standards developed by the European Committee for Standardization (CEN) and the European Committee for Electrotechnical Standardization (CENELEC) for operational compliance and by European Commission guidelines. In line with the New Legislative Framework logic, the chapter treats these standards and guidelines, together with emerging AI management system standards such as ISO/IEC 42001, as part of the governance toolkit that higher education institutions can use to become involved in the implementation of the legal obligations.

Beyond the legal analysis, the chapter translates the legal obligations into a practical tool to support compliance, identifying intervention points which are especially relevant in the context of collective bargaining (see Section 4). It also proposes sector-specific fundamental rights impact assessments (FRIA) and reporting mechanisms aimed at supporting compliance, worker participation and accountability in practice. All these elements could help HER institutions move from a legal reading of the Act to an approach oriented towards implementation that connects fundamental rights, labour and data protection law with the specific compliance architectures used in product safety and AI governance.

1. Stakeholders and the value chain under the AI Act in HER

AI systems in education must be analysed in terms of the sector's broader educational, technological and sociopolitical contexts. The integration of these systems – and of automation – is inherently political, shaped both by technology developers and by those responsible for its implementation (Williamson et al. 2023). The Act is built around the allocation of obligations to different actors in the AI value chain such as providers, deployers, importers, distributors and regulatory and oversight bodies. Identifying key actors is essential to allocate appropriate responsibilities.

Given that the education sector operates within a complex ecosystem, where public and private institutions intersect to deliver or support education services, clarifying the roles of stakeholders, as defined in the Act's Art. 3, is pivotal. Such clarity can improve compliance and accountability.

1.1 Providers

These are the entities that develop and supply the systems. This group may include EdTech, startups, the major technology corporations and, in some cases, universities or ministries of education when they develop or procure AI tools for widespread use. EdTech companies can also act as brokers, serving as intermediaries between higher education institutions, industry actors or government, guiding them in their procurement choices or acting as education providers (Ortegón et al. 2025).

Some examples illustrate this dual role: in Germany, IU International University of Applied Sciences developed Syntea, a personalised AI study assistant specifically trained on IU course materials and tailored for its students (IU International University of Applied Sciences 2025); similarly, the co-innovation project AI in Learning (2020-2021), funded by Business Finland, aimed to generate insights into human-machine interaction and the development of AI tools (AI in Learning 2021).

Providers not only shape the tools available to education, they influence how institutions adopt them. For these reasons, HER and other education institutions must review their procurement policies to ensure compliance with the Act. While education institutions often procure AI systems through public-private partnerships (Li Haoyang and Towne 2025), the Act does not set out specific procurement rules. However, to support public sector bodies in this task, including public universities, the European Commission (2024) has introduced model contractual clauses for AI procurement (MCC-AI). These are voluntary clauses that give minimum guidance, allowing public institutions to embed the Act directly into their contracts, complementing national procurement rules.

1.2 Deployers

Art. 3(4) of the Act defines a deployer as ‘a natural or legal person, public authority, agency or other body using an AI system under its authority except where the AI system is used in the course of a personal non-professional activity’. The Act thus ties the role of the deployer to the one which has ‘authority over such use’. Deployers must comply with the obligations outlined in Art. 26. As far as the workplace is concerned, deployers who are employers must, before using a high-risk AI system in a workplace, inform workers’ representatives and affected workers that they will be subject to that high-risk system (Art. 26(7)). In most cases, this includes universities and other education institutions. Given their central role, it is critical to distinguish deployers from providers, as providers bear more extensive regulatory responsibilities.

A notable challenge arises when deployers alter an AI system’s intended purpose (Art. 25(1)). In such cases, a university would assume the role of provider whereupon the provider obligations apply (Art. 16), including conformity assessment and CE marking where relevant. Universities will, however, usually act as deployers; they become providers only when they develop AI systems in-house or substantially modify an existing system’s intended purpose.

1.3 Importers and distributors

These are any natural or legal person in the supply chain, other than the provider, who introduces AI systems into the EU market or distributes AI-enabled educational technologies, for example retailers of boxed AI educational tools. They must ensure these systems comply with EU regulations and do not fall under prohibited practices prior to deployment.

1.4 Regulatory and oversight bodies

Institutions such as these also play a pivotal role. These include the national AI regulators and authorities responsible for implementing the AI Act within each Member State. Data protection authorities oversee compliance with both the Act and existing data protection laws, including the General Data Protection Regulation (GDPR). At EU level, the AI Office supports implementation and coordinates the national governance bodies.

A central unresolved issue is the allocation of responsibility and risk management within this intricate value chain, particularly for entities tasked with oversight and monitoring (Colonna 2022). For instance, if an AI system targets certain students as vulnerable groups (Art. 5(1)(b)) or inaccurately assesses an educator's performance (falling under Annex III or potentially triggering Art. 22 GDPR), determining liability – whether it lies with the education institution, the ministry of education or the provider – remains uncertain. HER institutions need to assess this in detail. Similarly, when AI-driven admissions processes unjustly reject applicants, questions of accountability and legal redress persist. Moreover, the Act relies on the wider quality infrastructure created by the EU New Legislative Framework, including notifying authorities, notified bodies, national accreditation bodies and market surveillance authorities. These actors may seem distant from day-to-day university practice, but they are relevant for the designation and oversight of the conformity assessment bodies, the supervision of the compliance of high-risk systems in the EU and the handling of any serious incidents that may also arise.

Education stakeholders need to define their role concerning AI systems clearly. Incorrect classification of the risk levels of an AI system can result in non-compliance and expose the university to legal and regulatory consequences.

Having identified the principal stakeholders and their respective legal obligations under the Act, the next section examines the limitations, focusing on prohibited and high-risk uses.

2. Scope of the AI Act in higher education

This section analyses how the Act applies to the HER sector, focusing on its risk tiers, prohibited practices, exceptions, high-risk uses and the general-purpose AI (GPAI) obligations.

The Act adopts a risk-based approach, categorising AI systems into four levels of risk: unacceptable (Art. 5); high (Art. 6); limited (Art. 50); and minimal or no risk, which are subject to very few, if any, specific obligations. It sets out obligations for providers and developers according to the respective risk category (Recitals 26 and 27). Which obligations apply depends on the institution's role in each use case. A key regulatory challenge is to ensure that AI systems used in education are subject to robust risk assessments and compliance mechanisms. Employers must invest in comprehensive legal and technical assessments to ensure accurate categorisation and robust compliance.

Several provisions of the Act will be significantly affected by the EC's Digital Omnibus legislative initiative released in November 2025 (European Commission 2025d). This remains at proposal stage and its final content and timing cannot be taken for granted.

2.1 Prohibited practices

When assessing the prohibitions set out in Art. 5, several applications are particularly relevant to the education sector:

- the use of subliminal manipulation or deceptive techniques that distort student behaviour and impair decision-making. For instance, tools that nudge students toward specific learning outcomes (Art. 5(1)(a))
- exploiting vulnerabilities based on age, disability or socioeconomic status, including tools that steer students into predetermined educational paths or influence their choices (Art. 5(1)(b))
- the use of AI systems for social scoring by public authorities, such as education ministries, is prohibited under Art. 5(1)(c)
- the use of facial recognition or biometric categorisation tools, such as fingerprinting or retina scanning, to infer sensitive personal characteristics (e.g. health, race, political views, religion, sexual orientation, etc.), or to monitor students (Art. 5(1)(e) and (g))
- AI systems used in classrooms or exam settings to infer students' emotional states or stress levels based on biometric data. These may only be permitted where required for medical or safety purposes (Art. 5(1)(f)). The European Commission's Guidelines on prohibited practices as defined by the AI Act (European Commission 2025a) are aimed at clarifying the prohibition, but its interpretation, as with the interpretation of the exception, remains ambiguous and could potentially create loopholes that undermine the original protections intended by the regulation.

2.2 The exception on prohibited AI systems inferring emotions

This subsection examines the narrow medical and safety exceptions to the prohibition of emotion recognition systems in education. The deployment of AI systems to infer emotions presents numerous technical, ethical and legal challenges. Emotions are not directly observable but may be inferred from contextual cues such as facial expressions, tone of voice, body language, cultural norms and situational context (Barrett et al. 2011; Mattioli and Cabitza 2024). Barrett – a neuroscientist – argues that no universal definition or consistent physiological or neurological pattern exists that can reliably distinguish specific emotions in a manner that AI systems could accurately detect (Barrett 2019).

AI systems claim to infer emotions or intentions through the analysis of biometric data including heart rate, muscle tension, body temperature, facial expressions, voice patterns and movement (Autoriteit Persoonsgegevens 2025). However, serious concerns exist about the scientific robustness of these technologies and their capacity genuinely to identify and measure an individual's internal emotional state (AI Act Recital 44; EPIC 2024; Gould 2024; Autoriteit Persoonsgegevens 2025: point 24). Beyond their contested scientific foundation, these systems may infringe fundamental rights, in particular the right to privacy under Art. 7 of the Charter of Fundamental Rights of the European Union (ECFR) and the right to data protection under Art. 8 of GDPR.

The prohibition on the use of AI systems to infer emotions in education institutions (and the workplace) stems from concerns related to power imbalance, their impact on fundamental rights and scientific and technical validity and reliability. Art. 5(1)(f) prohibits the use of such systems in education and training institutions at all levels, including vocational schools, and even during admission procedures (European Commission 2025a: point 255). Despite the broad prohibition, Art. 5(1)(f) allows these systems to be used, but only when strictly necessary for specific medical or safety reasons (European Commission 2025a: point 256). This is a narrow and strictly interpreted derogation.

The Commission articulates that 'emotions or intentions' should be interpreted broadly rather than restrictively (European Commission 2025a: point 247). The ban excludes the mere detection of 'readily apparent expressions, gestures or movements, unless they are used for identifying or inferring emotions', meaning that a raised voice or smile may not be prohibited, unless the data thus generated are being processed to identify or infer an emotion (European Commission 2025a: point 249). For example, logging that a student is whispering is outside the prohibition; classifying that whisper as 'anxious' or 'angry' is inside it. Also, as voice is listed as biometric data (European Commission 2025a: points 250, 251), a tonal analysis that infers emotions is inside the prohibition. Some borderline scenarios remain, such as the use of AI systems to infer emotions for purposes including preparing teaching materials in libraries, educator attendance monitoring, and in online and distance learning contexts (Autoriteit Persoonsgegevens 2025: point 21).

2.2.1 Medical exception

The Guidelines confirm that the medical exception applies only to those AI systems that are CE-marked medical devices under the EU Medical Device Regulation (MDR) and deployed under the supervision of qualified healthcare professionals for a specific and documented medical purpose (European Commission 2025a: points 256, 257). Applications related to general wellbeing, stress monitoring, wellness chatbots or emotional engagement do not qualify, and therefore remain prohibited.

The question also remains as to the conditions under which education institutions may deploy AI systems to monitor students' emotions for 'mental health support'. Commercial apps such as Woebot Health, Replika, Youper or Doro are marketed as providers of mental health support or companions (Punitham 2024), but fall within the prohibition in Art. 5(1)(f) when used in an education context.

In cases when the derogation applies, the deployer has the burden of proof. It must formally assess the specific use and document it, in consultation with the data protection officer and a qualified healthcare professional. This assessment must prove that the tool is a CE-marked medical device under the MDR and that its use is strictly limited to the certified medical purpose. Also, the national market surveillance authority has the power to verify the device's MDR certificate and the conformity of the deployment (Arts. 63-66). HER institutions invoking this exception must retain documented evidence of the device's certification and the specific medical purpose, and make it available on request to the competent authorities.

From an implementation perspective, this suggests that HER institutions could include an explicit 'no emotion recognition' clause in procurement contracts, with a narrowly framed exception procedure that mirrors the conditions in Art. 5(1)(f) and the Commission Guidelines.

Other questions may be raised, such as who determines what qualifies as a legitimate 'medical need' for deploying such systems? What role should ministries of education and health, or medical professionals, play in supervising their use? Beyond establishing valid legal exceptions, such applications may quickly transition into intrusive surveillance, infringing on privacy, dignity and body integrity.

2.2.2 Safety exception

The same line of reasoning applies to the safety exception which should always remain limited to what is strictly necessary and proportionate, and include a time limited scope (European Commission 2025a: point 259). Education institutions might want to justify the use of AI systems to infer emotions in classrooms or shared spaces under the premise of preventing violence or disruption (Autoriteit Persoonsgegevens 2025, point 21), but this is not enough. They need to demonstrate an objective life or health-related risk and demonstrate that no less intrusive alternative exists.

In conclusion, if the medical or safety exceptions are ever used to attempt to justify the deployment of such systems, a rigorous case-by-case investigation must take place to avoid opening the door to surveillance. Health and safety exceptions should not serve as backdoors for introducing emotion recognition technologies in education environments, which would undermine the rights of both students and educators.

2.3 High-risk use cases, classification and obligations

Under Art. 6(2), Recital 56 and Annex III (3), several AI systems used in educational contexts are classified as high-risk. The classification depends on the purpose of the systems, as defined by the provider (Art. 3(12) and assessed pursuant to Art. 6(2)). Not all AI systems deployed in education fall into the high-risk category, but those that may do so include systems to: (1) determine access, admission or assignment of individuals to education and vocational training institutions at any level; (2) evaluate learning outcomes, particularly when used to influence or guide the educational process within such institutions; (3) assess the appropriate level of education an individual should receive or is eligible to access; and (4) monitor and detect prohibited student behaviour during formal examinations or assessments. The prohibition does not cover general behavioural monitoring.

However, a derogation may apply. Under Art. 6(3) an AI system shall not be considered to be high-risk where it does not pose a significant risk of harm to health, safety or fundamental rights, including by not materially influencing the outcome of decision-making. It is not high-risk when it is intended to: (1) perform a narrow procedural task; (2) improve the result of a previously completed human activity; (3) detect decision-making patterns, or deviations from prior decision-making patterns, and does not replace or influence a previously completed human assessment, without proper human review; or (4) perform a preparatory task to an assessment relevant for the purposes of the use cases listed in Annex III.

Equally, under Art. 6(4), a provider who considers that an AI system is not high-risk under Annex III must document that assessment. To rebut the classification, the provider must show that the system is not high-risk and that it presents only minimal threat to health, safety or fundamental rights (Recital 53). The process applies only to providers and they must complete it before that system is placed on the market or put into service (Colonna 2022). Where the provider uses this rebuttal, the system and the justification must be registered in the EU database in accordance with Art. 49(2) and Art. 71, which allows the competent authorities and market surveillance authorities to scrutinise the reasoning and the supporting evidence.

Once classified as high-risk, both providers and deployers must comply with the legal obligations across the system's lifecycle. For implementation purposes it is useful to distinguish three layers of obligations: system-level requirements (Arts. 9-15); organisational quality management (Art. 17); and conformity assessment and CE marking procedures (Arts. 43, 47-49).

Compliance with the legal obligations may be demonstrated by conformity with harmonised standards (Art. 40) or common specifications where standards are not available or are insufficient (Art. 41). However, following harmonised standards is not mandatory and other means to demonstrate compliance remain possible. Once deployed, providers must develop a system for post-market monitoring (Art. 72), implement corrective actions to restore compliance (Art. 20) and establish a system to report serious incidents to the competent authority (Art. 73). The Commission's guidance and reporting template on serious AI incidents will shape how these duties are implemented in practice and will be relevant for HER institutions that develop or adapt high-risk systems (European Commission 2025c).

Deployers must take appropriate technical and organisational measures to ensure the use of such systems is in accordance with the instructions for use accompanying them, and assign human oversight to people with the necessary competence, training and authority and support (Arts. 26(1), 26(2)). If deployers identify a serious incident, they must immediately inform the provider, the importer or distributor and the market surveillance authorities (Art. 26(5)). As outlined in Section 1.2, there are clear rights of information benefiting workers and their representatives (Arts. 26(7), 26 (11)).

The Act does not provide guidance on how education institutions should implement these obligations across the educational lifecycle. To comply, higher education institutions must conduct comprehensive internal assessments. Here, in general, trade unions should be proactively involved in assessing that the classification process is aligned with the principles of transparency for affected persons and accountability, especially under Art. 14(3)(b); Art. 27 ECFR; Directive 2002/14/EC for informing and consulting employees; and Art. 35(9) GDPR. This can be translated into interventions during procurement, by requesting transparency and documentation on the system functionality and risks, and by participating in impact assessments and human oversight mechanisms; and, after deployment, through involvement in monitoring such as participating in system audits or reviews. In addition, trade union input can address issues such as performance evaluation criteria, data use, monitoring practices, workload allocation and decision-making procedures, particularly when these influence working conditions, autonomy and labour and data protection rights.

Moreover, classifying AI systems is not straightforward as some educational AI applications fall into grey areas. For instance, AI teaching support tools that analyse lesson plans may not typically qualify as high-risk unless they influence decisions on student evaluation or access. Here, classification depends on the system's actual function, not on its technical capabilities or model type. Where doubt arises, providers or deployers should conduct case-by-case assessments and ensure that compliance mechanisms and internal governance models evolve accordingly. Trade unions can play a key role in reviewing these uses and ensuring governance frameworks protect staff and students, and that systemic risks are assessed where applicable.

2.4 General-purpose AI systems in higher education institutions

Large language models (LLMs) and other GenAI technologies have introduced both transformative potential and complex challenges for the sector. In response, universities have developed diverse internal guidelines to govern their use (Jiao et al. 2024; Ponce del Castillo and di Ridolfo, this volume).

The AI Act defines a general-purpose AI model (GPAI) as one that is 'trained with large amounts of data using self-supervision at scale, that displays significant generality and is capable of competently performing a wide range of distinct tasks regardless of how it is placed on the market and that can be integrated into a variety of downstream systems or applications' (Art. 3(63)). Recitals 98 and 99 clarify that large generative models across text, image and sound modalities typically meet this definition. GPAI is a regulatory category based on functional scope, not model architecture or generative capacity. However, its definition remains contested. Some commentators have criticised the European Commission's formulation for blurring the lines between GPAI, GenAI and artificial general intelligence. This chapter adopts the term GPAI in line with the legal definition in the Act.

GPAI use in HER institutions is not automatically high-risk; classification depends on the specific function and whether it falls under Annex III. It is important to distinguish between a 'general-purpose AI model' (Arts. 53-56) and a 'general-purpose AI system', which incorporates such a model into a given application.

GPAI model providers must meet transparency and documentation requirements, are encouraged to draw up codes of practice (Arts. 53-56) and must comply with other rules on copyright and data protection. Such models are not inherently low risk.

The level of regulatory obligations depends on the specific use to which the model is then put downstream.[1] When integrated into high-risk applications under Annex III, corresponding obligations apply, along with the compliance obligations set out in Arts. 53-54. These obligations apply – including to universities and research institutions – as from 2 August 2025, one year earlier than the planned date for application of the rest of the Act.

If the model meets the criteria for posing a 'systemic risk' under Art. 51, due to its scale or impact, it becomes subject to additional obligations under Art. 55 such as performing model evaluations and reporting incidents.

To support implementation, other measures have been and will be published, including the work of the AI Office (2025a, 2025b) in putting out a template summarising training content for GPAI models, a code of practice and, within the latter, a form for disclosing what data was used to train the model (relevant for bias, discrimination, copyright, etc), its intended uses and what it cannot do. HER institutions should treat these instruments as levers in procurement and governance. When contracting GPAI providers or platforms, universities can require completion of the AI Office documentation templates, link them to internal registers of AI systems and use them to inform data protection and fundamental rights impact assessments and AI literacy initiatives.

When a GPAI model is used in student admissions, automated grading or exam monitoring, the regime of high-risk obligations applies (risk management, data governance, documentation and record-keeping, human oversight and conformity assessments). Where GPAI is integrated into high-risk applications, the relevant obligations apply; otherwise, only the use-specific duties (Arts. 50-51, where applicable) are engaged.

Finally, training and deploying GPAI models require large amounts of energy and other environmental resources which the Act does not regulate. This raises questions for HER institutions relating to environmental responsibility and commitments to climate and sustainability. The regulation's lack of detailed provisions and measures on resource use transparency, lifecycle assessment and sustainable AI technologies means that institutions must rely on sector-specific measures to manage sustainable AI deployment.

3. AI literacy in the context of education

As a fundamental requirement, the Act obliges both providers and deployers to ensure, to their best extent, an adequate level of AI literacy among staff and relevant stakeholders, meaning the necessary capacity to make informed decisions regarding AI systems (Recital 20; Art. 4). This obligation applies to providers and developers and is framed as a fundamental requirement rather than an enforceable obligation, characterised by two key features.

1. Here again, as described earlier, a university that repurposes or substantially modifies such tools will be considered a provider and must comply with the corresponding obligations.

First, it is context sensitive. AI literacy efforts must be tailored to reflect staff expertise, operational roles and oversight functions. Art. 4 does not prescribe any specific training methods, format or duration, leaving room for flexible implementation. However, Recital 20 refers to the acquisition of the capacity to understand the correct application of technical elements during the development phase to enable workers critically to understand the functioning and limitations of AI systems and how decisions taken with the assistance of AI will have an impact on them.

Second, the obligation is broad and non-prescriptive. Providers and deployers retain discretion over how literacy initiatives are delivered. However, this discretion cannot be used to deliver minimal or tokenistic training. Importantly, there is no presumption of compliance simply by having mirrored the good practice described in the Commission's living repository in this area (European Commission 2025b); this serves as a learning and exchange resource but does not constitute a compliance mechanism.

From a labour law perspective, AI literacy is not a peripheral activity but a core element of workplace rights. AI literacy must be understood within the broader obligation of employers to provide adequate information to workers about which systems are deployed, for what purposes and with which risk classification, and to equip workers with the means to contest such systems. AI literacy should extend beyond technical skills to include legal and rights awareness (GDPR, copyright and fundamental rights), critical thinking and training on oversight mechanisms and ethics. Collective agreements and social dialogue processes should explicitly incorporate AI literacy obligations to ensure that staff can participate meaningfully in the governance of AI in their workplace.

In the HER sector, several key questions that remain unresolved: how can educators contest or override AI-generated recommendations or decisions? And what oversight mechanisms enable staff to monitor decisions affecting students or themselves?

The Act does leave regulatory gaps in respect of higher education institutions. While it places the responsibility on them to develop tailored literacy frameworks, those acting solely as deployers are subject to proportionate (and lesser) compliance. Universities developing or commercialising AI systems are subject to stricter obligations, as discussed above. No EU guidelines on AI literacy are foreseen, so the main instruments are the legal text itself and the non-binding living repository (European Commission 2025e).

Beyond the Act, education stakeholders have proposed alternative AI literacy frameworks. The Rutgers Critical AI Literacy Working Document (Goodlad and Stoerger 2024) outlines a values-based approach, emphasising epistemic authority, bias and power. Educause frames AI literacy as a pedagogical imperative, focusing on student agency and curricular integration (Kassorla et al. 2024). Similarly, the AI Competency Framework developed by the United Nations Educational, Scientific and Cultural Organization (UNESCO) (UNESCO 2024) offers a global benchmark for student skills covering ethical, technical and civic dimensions. These approaches go beyond the Act's minimum literacy requirements, by incorporating ethics (Müller 2020), and underscore the need for sector-specific governance aligned with fundamental rights and democratic accountability.

4. A compliance checklist for the HER sector

The following checklist translates the AI Act's obligations into a structured, phase-by-phase tool for higher education and research. It takes into account the Commission's Guidance on prohibited practices (European Commission 2025a) and its Guidance and reporting template (European Commission 2025c),[2] and also distinguishes duties by role (provider, deployer or both), identifying when specific legal provisions are engaged. In addition to guiding institutions through compliance steps, the checklist enables regulators, worker representatives and other oversight bodies to track actions taken, assign responsibility and verify alignment with the statutory requirements. By combining clarity on the legal obligations with human oversight and documentation, it supports both proactive governance and effective regulatory monitoring.

Table 6.1 **AI Act compliance checklist for higher education and research**

Step/question	What should be done?	Key AI Act articles, GDPR, other EU law
Phase 1 Before procurement or development of an AI system		
1. Identify your role(s)	Are you a provider, a deployer or both? If the university develops AI in-house or makes substantial modifications, it becomes a provider. Otherwise, it is a deployer Who is buying the AI systems?	Definitions: Art. 3 Obligations: Art. 16-29 provider Art. 26: deployer Art. 28: substantial modification MCC-AI for public procurement
2. Who will be affected?	Applies to provider and deployer Identify which groups of individuals will be exposed to AI systems: students, academics, researchers, administrative staff, etc.	Document the affected populations Art. 9: required for risk assessment
3. Make inventory of AI systems	Applies to provider and deployer List all AI systems in use or under development. Include 'shadow' IT (unapproved tools) Identify any outside institutional approval processes	Art. 11: technical documentation Annex IV
3.1 Type of systems	What systems are being purchased and deployed? Are the AI systems sufficiently documented? Are they able to learn during their use?	Art. 3(1) Art. 12-13 GDPR
4. Does the system involve a prohibited practice?	Applies to provider and deployer Some practices are absolutely prohibited (Art. 5(1)); others only allowed in limited law enforcement contexts (Art. 5(2)-(3)) Check for: emotion recognition, biometric categorisation, social scoring, manipulative nudging or profiling that exploits vulnerabilities (age, disability, socioeconomic status) If yes ⟶ STOP	Art. 5(1) EC guidance on prohibited AI practices

2. The latter of which remains draft at this stage.

5. Inform workers and trade unions	Applies to deployers	Art. 26(7): inform affected workers
	Inform and, when relevant, consult workers and their representatives. This is also relevant under labour law	Art. 26(11): inform persons about automated decisions Art. 27 ECFR Dir. 2002/14/EC: information & consultation GDPR Art. 35(9)
6. Develop AI literacy	Applies to provider and deployer	Art. 4 Recital 20
	Covers both general principles and guidance	Guidance
	Provide AI risk and rights training to relevant staff (researchers, teaching assistants, IT, legal, pedagogical staff). Link to general principles in Art. 4 and Recital 56	
Phase 2 Before deployment		
7. Is the use high-risk?	Applies to provider and deployer	Art. 6 Annex III(3)
	If the system involves admissions, assignment, evaluation or monitoring during exams	Art. 6(3), (4)
	Deployers rely on the provider's classification; they cannot self-exempt under Art. 49(2)	
7.1 High-risk presumption rebuttal, evidence-based *Only possible before placing on the market; requires documented justification	Applies to provider	Art. 6(3), (4)
	If a system falls within a use case listed in Annex III (presumptively high-risk), but does not pose a significant risk to health, safety or fundamental rights, or does not materially influence the outcome of decision-making, or the provider considers, through a documented risk assessment, that it is not a high risk, then it may be exempted from high-risk classification	
	The provider must register the system and the justification for exemption in the EU database	
8. If the system is high-risk, have you done the following?	Applies to deployer	Art. 27: FRIA
	Conduct an ex ante fundamental rights impact assessment; set up human oversight	Art. 14: human oversight
	Align with other impact assessments on data protection and occupational safety and health	
	If a public body, register deployment in the EU database (this is separate from the provider's system registration)	Art. 49(1a) Registration in EU database
	Applies to provider	
	Complete conformity assessment, affix CE marking and register the system in the EU database	Art. 43: conformity Art. 49: registration/CE Art. 51: EU database
	Maintain full technical file	

9. How will compliance be demonstrated?	Applies to provider Use of harmonised standards from CEN-CENELEC Joint Technical Committee 21 or common specifications when no standards exist for operational compliance. If neither is used, justify equivalent controls	Arts. 40-41
	Applies to deployer Deployers must follow the provider's instructions for use and must also monitor, perform human oversight and abide by other obligations Ensure that technical documentation is accessible to the competent authorities upon request	Art. 26 Annex IV
10. Does it use a general-purpose AI model (GPAI)?	Applies to provider Clarify whether you are just using the model (deployer) or modifying it (become a provider) Ensure transparency compliance Providers must publish a training data summary	Art. 3(63): Definition Arts. 53-56: GPAI obligations AI Office template for GPAI providers
11. Transparency obligations for systems intended to interact directly with natural persons	Applies to deployer Label AI-generated outputs (e.g. deepfakes) Inform users when they interact with AI Verify that the provider publishes a summary of copyrighted training data If the model is designated as systemic risk GPAI, ensure compliance with Art. 55	Arts. 50-51
12. GPAI provider duties	Applies to provider Publish training data copyright summary Manage model risks Comply with systemic risk rules if designated by the AI Office	Arts. 53-56
13. Access to regulatory sandboxes	HER institutions can apply to participate in national sandboxes set up by Member States to experiment and test AI tools	Art. 57
Phase 3 Deployment		
14. Internal governance in operation	Applies to deployer Use the system per provider instructions; ensure human oversight; monitor performance; keep required record logs; report serious incidents Create policies & procedures for documentation, risk management, accountability oversight	Art. 26 Arts. 50-51 transparency where applicable
	Applies to provider Implement: • risk management: Art. 9 • data governance: Art. 10 • technical documentation: Art. 11 & Annex IV • record-keeping: Art. 12 • transparency: Art. 13 • human oversight: Art. 14 • accuracy, robustness, cybersecurity: Art. 15 • quality management: Art. 17	Chapter III High-risk obligations

Phase 4 Ongoing monitoring & improvement		
15. Monitor, document, review, improve	Applies to provider	Arts. 72-74 Art. 73
	Postmarket monitoring of the system; update documentation of performance; implement corrective actions; report serious incidents to authorities (Art. 74)	Art. 20
	Cooperate with market surveillance authorities upon request (Art. 75-76)	
	Consult European Commission reporting template on serious AI incidents to identify potentially harmful patterns or other important risks of high-risk AI systems at an early stage	Commission Guidance on reporting serious AI incidents
	Applies to deployer	Art. 4 Art. 26(6)
	Continuously monitor use; document issues; report serious incidents to the provider and competent authority; mitigate risks	Recital 56
16. Communicate	Applies to provider and deployer	Recital 56; Art. 4.
	Ongoing communication, AI literacy and training for staff and students	

Source: author's own elaboration.

It should be noted that the AI Act applies in phases. As from 2 February 2025, the prohibitions and the obligation regarding AI literacy are in force, while the obligations on GPAI took effect from 2 August 2025. The main provisions on high-risk AI systems will apply as from 2026, possibly with additional enforcement mechanisms through 2027. This staggered timeline allows all actors across the AI value chain time to prepare their compliance procedures and documentation.

Conclusion: a message to regulators

The governance of AI systems within higher education and research can only be effective when the horizontal rules in the AI Act are complemented by sector-specific frameworks, both at EU and national level. This dual perspective is required by EU law, as education remains a competence of Member States under Articles 165-166 of the Treaty on the Functioning of the European Union, which must also be interpreted consistently with the fundamental rights laid down in ECFR, in particular Article 14 (the right to education) and Article 21 (non-discrimination).

The case of education demonstrates why this interaction is essential. Given the heterogeneity of the sector, a one-size-fits-all approach to risk in the context of AI governance is likely to result in uneven implementation. Risks can have an impact not only on universities as organisations but also on academic and administrative staff, particularly when AI tools affect and reshape workload, time, performance assessment, surveillance or recruitment.

As it stands, the interpretation and implementation of the AI Act, the harmonised standards and the soft law accompanying it, chiefly in the Commission's Guidelines on prohibited practices, raise several sector-specific challenges for HER: (1) transparency of procurement processes; (2) allocation of responsibilities across the value chain; (3) safeguards to ensure human oversight and preserve the authority of educators, allowing institutions and worker representatives to participate in such procedures; (4) ambiguity over prohibited uses such as emotion recognition in classrooms or during interviews and examinations; (5) unclear understanding of the reach and substance of AI literacy; and (6) liability in cases of harm or rights infringements linked to the use of AI. In the absence of this, compliance may become inconsistent and discretionary, undermining legal certainty and fundamental rights.

Additionally, AI governance also requires sectoral operationalisation of the law. The AI Office can play a coordination role within its current mandate. In cooperation with the Fundamental Rights Agency, the AI Office could develop harmonised, sector-specific tools like a FRIA template and audit methodologies for education institutions, leaving national authorities to adapt them to local circumstances. Structured consultation with workers and their representatives should be built into the process. A FRIA template would provide clarity, reduce administrative burdens and ensure that risks are systematically identified, mitigated and monitored. To reinforce accountability in the sector, HER institutions should also publish annual reports on data processing, the impact of AI on workloads, working conditions, pedagogical autonomy and academic freedom, submitting these for public review and oversight. Practical instruments like the phase-by-phase AI Act checklist presented in this chapter can complement these measures. This is not only a compliance aid for institutions and a monitoring tool for trade unions, but also a ready-to-use oversight instrument forming a roadmap that can help the authorities verify compliance, identify gaps and promote the consistent application of the AI Act across the HER sector.

EU regulators should further refine the sector-specific implementation of the AI Act by issuing tailored guidance for HER, integrating workers' data and social rights into impact assessments and making social dialogue a key component of AI governance. This would ensure that workers are not only consulted but have the capacity to embed systematic mechanisms for participation and the negotiation of the data-driven tools that are being introduced into their workplaces. This would foster engagement of the social partners, reinforce the protection of fundamental rights and improve technological accountability.

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Abbreviations

AI	Artificial intelligence
CEN	European Committee for Standardization
CENELEC	European Committee for Electrotechnical Standardization
ECFR	Charter of Fundamental Rights of the European Union
EdTech	Educational technology (industry)
EU	European Union
FRIA	Fundamental rights impact assessment
GDPR	General Data Protection Regulation
GenAI	Generative AI
GPAI	General-purpose AI
LLM	Large language model
MCC-AI	Model contractual clauses for AI procurement
MDR	Medical Device Regulation
UNESCO	United Nations Educational, Scientific and Cultural Organization

Chapter 7
Copyright and generative AI – considerations for educators

Kari Kivinen[1]

Introduction

The increasing use of digital e-learning materials has prompted educators to question their rights to their lesson plans, teaching materials, presentations and other creative works. While the creator normally owns the copyright to their work, an employer may acquire rights to an employee's work through a separate agreement.

Copyright, a branch of intellectual property (IP) rights law protecting literary and artistic works, also covers the creations of educators. It applies automatically on creation and does not require registration for protection. However, there are two key conditions. First, *originality*: the work must be based on the author's own intellectual creation, reflecting their free and creative choices with a personal touch. Second, *expression:* the work must be expressed in a form that is identifiable with sufficient precision and objectivity.

Educators also face legal uncertainties about using copyrighted digital content to enhance their teaching. Article 5 of the Directive on Copyright in the Digital Single Market (DSM Directive) within the European Union (EU) permits the use of digital works for teaching, without needing prior permission from the rightsholder, provided certain conditions are met.[2] These can be summarised as follows:

– *purpose*: use must be for non-commercial purposes;
– *environment*: use within the education establishment (e.g. whiteboards) on its premises or at other venues, or through a secure electronic network accessible only to students and teaching staff (intranet, virtual learning environment, virtual classrooms);
– *attribution*: is accompanied by the indication of the source, including the author's name, unless this turns out to be impossible. This provision aims to provide educators and students with the legal certainty to use protected content in their digital teaching activities. However, due to the territorial nature of copyright laws, EU Member States have implemented this exception in slightly different ways.

1. The views expressed in this article are those of the author and do not necessarily reflect the position of the European Union Intellectual Property Office.
2. In the US, 'fair use' is a broad legal principle that permits certain uses of copyrighted material, such as in education, criticism or commentary, without the need for permission. This is determined on a case-by-case basis. In contrast, the EU does not recognise a general concept of fair use. Instead, Article 5 of the DSM Directive provides specific exceptions, such as the permitted use of digital works for teaching purposes, but only under certain clearly defined conditions.

The European Union Intellectual Property Office (EUIPO) is the EU agency responsible for managing trademarks and designs and supporting policy development on intellectual property. It puts an emphasis on bridging copyright theory and practice. It has published a set of frequently asked questions (FAQs) on copyright for educators (EUIPO 2023) which provides practical information on using copyright protected content in education and training, particularly online. It also explains how copyright protection can benefit them as potential creators of works in the context of education. Answers to the FAQs are provided for all EU Member States and are available in English and/or at least one official language of each Member State. EUIPO has also published a practical interactive guide to understanding the copyright implications of generative AI in education. It translates abstract legal provisions, such as some of the DSM Directive's teaching exceptions and the AI Act's transparency requirements, into actionable steps for educators (EUIPO 2024).

This chapter provides an overview of the interaction between copyright law and generative AI tools in education and the implications for educators and students in the European Union. It outlines the framework of the EU's copyright protection for teaching materials and highlights the dual challenges introduced by the use of generative AI that relies on or produces copyright-protected content. Particular attention is given to the practical and normative challenges that arise from the use of copyrighted content to train AI models, the disclosure of AI-generated outputs and the need for transparency when these technologies are integrated into teaching and research activities.

1. Challenges of generative AI on copyright in education

1.1 Generative AI: an education challenge

Like other emerging technologies, generative AI offers solutions in a number of areas designed to support and enhance human capabilities. Given the rapid evolution of AI technologies, education and training providers need to consider carefully how and when AI systems can be used responsibly and in the public interest, especially when they involve the processing of personal data or copyright protected materials.

From an education provider's perspective, it is important to promote the acquisition, development and deployment of trustworthy AI systems and to ensure that all users – educators, staff and students – are adequately trained in the use of AI and in monitoring its operation and use. The acquisition and use of AI services raises many ethical and legal issues, including copyright ones.

1.2 Generative AI: a copyright challenge

Generative AI, capable of creating text, images and music with or without human assistance, holds immense potential. But behind its creative power lies a host of legal uncertainties regarding the application of copyright law. Additionally, the training of these models often involves large amounts of potentially copyrighted material scraped from the internet – that is, the automated extraction of content from internet websites using software. While some of this use may be lawful under the EU's text and data mining exceptions in Arts. 3 and 4 of the DSM Directive, the lack of transparency about what data has been used and whether rightsholders' opt-outs have been respected creates significant legal uncertainty and other complex legal and ethical issues (Dornis and Stober 2025).

The difficulty in knowing what data AI models have consumed complicates the assessment of possible copyright infringement. Lawsuits are already being filed, with artists and publishers challenging the use of their work in education. The most followed of these lawsuits is the New York Times case against OpenAI. In its defence, OpenAI has provided an interesting response (Chadwick 2024):

> Because copyright today covers virtually every sort of human expression – including blog posts, photographs, forum posts, scraps of software code, and government documents – it would be impossible to train today's leading AI models without using copyrighted materials. (Milmo 2024)

Other recent cases confirm the breadth of these disputes: French authors and publishers against Meta in 2025 (International Publishers Association 2025); and, in the US, cartoonist and illustrator Sarah Andersen and others v Stability AI, alleging copyright infringement, right of publicity violations and other claims related to the use of the artists' works in training datasets for AI image-generating platforms (Kwon 2025).

In response, news outlets are increasingly blocking AI crawlers – that is, automated software agents deployed to collect large amounts of data from the internet. These practices have led to new types of concerns and there is a lack of legal certainty on how rightsholders should implement the technical solutions (via opt-outs) that exist to prevent their copyrighted content being scraped. According to Wired, 88% of top-ranked news outlets in the US block web crawlers (Knibbs 2024), while the Reuters Institute reports that nearly half (48%) of the top news websites across the ten countries in the study were blocking OpenAI's crawlers (Fletcher 2024). It is important to remember that blocking all crawlers may prevent legitimate search engines from indexing the site and may damage the site's visibility in search engines.

The outputs of generative AI tools, typically in response to simple prompts, are increasingly used to assist innovative, creative, branding and other information and knowledge activities. These outputs raise a distinct set of copyright issues that differ from those arising at the training stage of the models: do works generated with limited or no human input meet the originality threshold required for copyright protection? Who owns creativity? Does traditional copyright law apply or are new solutions needed? For universities and educators, these issues are particularly relevant when AI-generated content is integrated into teaching materials or research outputs.

Generative AI can be a new tool in the hands of human creators, but work outputs generated entirely by AI with limited or no human input cannot be protected by copyright. This follows the case law of the Court of Justice of the European Union

(CJEU), which defines a ‘work’ as the author’s own intellectual creation reflecting free and creative choices.[3]

Creators have also expressed concern that AI-generated work might copy their style or ideas. In response to such concerns, Art. 53(1) of the AI Act requires the providers of general-purpose AI (GPAI) models to: (1) prepare and maintain detailed technical documentation about the model; (2) provide transparency information to the downstream AI system providers who intend to integrate it; (3) ensure compliance with EU copyright and related rights laws; and (4) publish a sufficiently detailed public summary of the training content used to develop the model. This would help protect creators and make things clearer, but it is still relatively unclear how AI can be prevented from infringing copyright and what penalties should be applied and by whom.

In parallel with Article 53, in July 2025 the European Commission published a voluntary code of practice for providers of GPAI models – that is, the companies developing and training large AI models. The code provides a structured way to disclose the categories of data used, while aiming to enhance the transparency ‘needed to facilitate the exercise of [rightsholders’] fundamental right to intellectual property and the fundamental right to an effective remedy in the enforcement of their rights’ (European Commission 2025). This aims to require AI developers to detect and respect the machine-readable opt-outs made by rightsholders under Article 4(3) of the DSM Directive. The specific chapter on copyright contains three key measures: (1) signatories should identify and comply with rights reservations when crawling the World Wide Web; (2) they should mitigate the risk of copyright-infringing outputs; and (3) they should designate a point of contact for electronic communication with affected rightsholders and enable the lodging of complaints.

These provisions are particularly relevant for education and research, where institutions rely on third-party AI systems and need clarity on whether the models they use have been trained in a manner that respects copyright law. Universities, as deployers, may use the code of practice as a benchmark or due diligence tool to evaluate external AI services. If issues arise (e.g. plagiarism claims or IP disputes involving AI-generated content), universities or other education institutions could have access to more information.

2. Generative AI copyright issues for educators and students

The ever-increasing use of generative AI tools is transforming university practices, offering new possibilities for research and education. However, the ethical implications of using this powerful technology must be carefully considered.

Users need to be aware that AI services may collect data from all the inputs and prompts into their databases to train the tool further. The same can happen when students submit

3. CJEU judgements in *Eva-Maria Painer v Standard VerlagsGmbH and Others* (Case C-145/10, ECLI:EU:C:2011:798), para 88; *Sociedade de Vestuário SA v G-Star Raw CV* (Case C-683/17 ‘Cofemel’, ECLI:EU:C:2019:721), para 30.

their work for plagiarism checks. One must be especially careful with sensitive data, so choosing AI tools with strong proven data security practices is paramount. These tools should guarantee that data is *not* stored or reused for the purposes of further training. It is important to remember that most student work is also copyrighted material. Moreover, users should ensure that any AI tools they use comply with copyright laws and relevant licences (EUIPO 2024).

Disclosing the origin of AI-generated content in research, articles or teaching is recommended to avoid plagiarism concerns. In view of the complex issues surrounding copyright in general, and the implications of generative AI in particular, EUIPO is considering becoming more involved in this area, as part of its new 2030 strategic plan, to support the strengthening of the IP ecosystem in line with ongoing technological developments. This should make it possible to develop useful information on the implications these developments have for different types of audience and certainly for educators. A forthcoming Copyright Knowledge Centre, a central hub for information, good practice and dispute resolution in the field of IP and new technologies, is planned to equip copyright holders with clear, practical information on how their works may be used in the development of generative AI, and how they can effectively manage and protect their intellectual assets. It is highly important that AI developers themselves ensure that the content generated through their services is detectable in a machine-readable format (EUIPO 2025).

Conclusion

The integration of AI systems into teaching and research environments introduces exciting opportunities while simultaneously generating legal and ethical questions. In particular, copyright compliance, the confidentiality of information and data protection are key concerns. As generative AI tools become embedded in educational practice, it is essential that educators and students understand the implications of their adoption and use. This encompasses the provenance of training data, the limits of permissible text and data mining and the legal status of AI-generated outputs.

Respect for EU copyright law, especially the reservation of rights under Arts. 2 and 4 of the DSM Directive and the treatment of text and data mining output, are a baseline for lawful use. It also important to ensure transparency regarding the use of generative AI, including the disclosure of AI-assisted contributions and the verification of outputs vis-à-vis accuracy and potential infringements. These safeguards need to be embedded in clear institutional policies that are aligned with the EU regulatory framework and the guidance from EU bodies, extending to the obligations under Article 53 of the AI Act and the commitments encouraged by the code of practice for GPAI models.

The effective use of generative AI in education will depend on a combination of internal policies, capacity building for educators and students, and guidance from the EU institutions – all of which are crucial in ensuring that these technologies are used in ways that support education while upholding fundamental rights.

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Abbreviations

AI	Artificial intelligence
CJEU	Court of Justice of the European Union
DSM	Digital single market
EU	European Union
EUIPO	European Union Intellectual Property Office
FAQ	Frequently asked question(s)
GenAI	Generative AI
GPAI	General-purpose AI
IP	Intellectual property

Chapter 8
The impact of generative AI on the intellectual property rights of academics: a trade union perspective

Petri Mäntysaari

Introduction

General-purpose AI (GPAI) models (see e.g. Galanos and Stewart 2024) need to be trained on vast amounts of text, images, videos and other data. Training data may include copyright protected content (European Commission 2025a: point 4; Marcelin and Cassetti 2025; Kivinen, this volume).

The impact of generative AI (GenAI) on the intellectual property (IP) rights of academics has emerged as a cause of concern (UNESCO 2023: 36; Kretschmer et al. 2024). From a trade union perspective, this question should be studied through the lens of union values and the professional needs of academics.

Views on artificial intelligence (AI) are generally based on values (Rudschies et al. 2021: 6; UNESCO 2021a: 32; Holmes et al. 2022: 9). So are policies on higher education (Bologna Process 2020, 2024b) and, in addition, the policies of higher education trade unions. The member unions of the European Trade Union Committee for Education (ETUCE) are expected to share 'the vision, purpose and contribution of free, universal, public, high-quality education for the development of more equitable, fair and democratic societies' (ETUCE 2021: 5). The concrete ways to reach such broad goals include making teaching careers attractive (Education International 2024) and protecting academic freedom (ETUCE 2020). Unions are expected to address their members' professional needs (Bascia and Stevenson 2017: 55-59) and recognise their diversity (ETUCE 2021: 9-10).

Because of their diverse roles in higher education, academics have varied professional needs relating to IP rights. Academics create or co-create protected works as educators and researchers. Academics use protected works in teaching and research. Moreover, academics evaluate the quality of academic and student work and act as the guardians of scientific integrity and a scientific worldview.

The combination of diverse professional needs and values means two things for trade union policies that address GenAI and IP rights. First, the objective of trade union policies should be to reach the best possible outcome for every member in each of the member's roles, to the extent that this is possible without prejudice to the interests of other members or roles. Second, from a trade union perspective, IP rights and GenAI policies are tools to achieve greater goals. Unions need to take a holistic perspective and focus on all the complementary ways they have of achieving these goals. For this reason, trade unions' IP or GenAI policies should never be limited to IP or GenAI alone.

This chapter discusses these questions when academics are authors of protected works (Section 1), users of GenAI tools in research (Section 2), users of GenAI tools in teaching (Section 3) and as guardians of scientific integrity and a scientific worldview (Section 4). It focuses on international law and European Union (EU) law, as the legal frameworks which have the most impact in a European perspective, and is particularly concerned with copyright.

1. Academics as authors of protected works

The prime copyright owner is the author. The United Nations Educational, Scientific and Cultural Organization (UNESCO) recommends that copyright be regarded as an essential component of academic freedom (UNESCO 1997: para. 12; UNESCO 2017: 37). For the same reason, works created by academics ought not to fall within the scope of the 'employer exception' or the 'work-made-for-hire' doctrine applicable in some countries (AAUP 2014; Carlson 2015; Willinsky 2023: 114-117).

The main rule is that the training of an AI model requires authorisation from copyright holders in the EU. Copyright holders have an exclusive right of reproduction, based on Art. 2 of Directive 2001/29/EC on the harmonisation of certain aspects of copyright and related rights in the information society (InfoSoc Directive) and is interpreted broadly.[1] Any digital copy can amount to a reproduction, while changes made in the collected material can amount to an adaptation within the scope of the exclusive right. Both reproduction and adaptation in the training of GenAI can infringe copyright holders' economic rights (Kretschmer et al. 2024: 111).

However, EU law also fosters this training in three main ways (Regulation (EU) 2024/1689, Recital 105; Kretschmer et al. 2024: 126). First, there are limitations to the copyright holder's exclusive right of reproduction within the InfoSoc Directive. The exclusive right does not cover certain temporary acts of reproduction that have 'no independent economic significance' (Art. 5(1)). Second, copyright holders may license the use of their works for the purposes of text and data mining (TDM) or otherwise (Directive (EU) 2019/790 on copyright and related rights in the digital single market (DSM Directive), Recital 18; EUIPO 2025: 98). Third, the DSM Directive permits TDM with no compensation to copyright holders under some circumstances (Recital 17 and Arts. 3-4) and, while it sets out fundamental exceptions, these are subject to limitations.

The limits to permitted TDM under the DSM Directive depend on whether mining is being done for scientific research (Art. 3) or other purposes (Art. 4). In both cases, it is subject to a 'lawful access' requirement (Art. 3(1) and 4(1)). Moreover, opt-outs are possible when mining is for purposes other than scientific research. The general TDM exception applies 'on condition that the use of works and other subject matter … has not been expressly reserved' by the copyright holder 'in an appropriate manner, such as machine-readable means in the case of content made publicly available online' (Art. 4(3)). Such restrictions are complemented by the AI Act (Regulation (EU) 2024/1689;

1. CJEU, Case C-5/08 *Infopaq International A/S v Danske Dagblades Forening*, paras. 40-43.

Peukert 2024) which states that, where the provider of a GPAI model places the model on the market, it must put in place a policy to comply with EU law on copyright and related rights, in particular to identify and comply with the reservation of rights. It is mandatory to use state-of-the-art technologies for this purpose (Recital 106 and Art. 53(1)(c)). When copyright holders reserve their rights, markets are created for content licensing and technical solutions (EUIPO 2025: 98). Academics that reserve their rights can benefit when demand for high-quality data increases (EUIPO 2025: 13 and 100-102). The protection of copyright gives them better incentives to publish research (Peukert et al. 2025).

As authors of protected works, academics might benefit indirectly from the Commission's Guidelines (European Commission 2025a) and the EU's general-purpose AI code of practice (European Commission 2025b). Both are designed to foster copyright compliance within the AI Act: the Guidelines clarify the scope of the obligations for providers of GPAI models; the GPAI code helps demonstrate and assess compliance with the obligations set out in Arts. 53 and 55 (European Commission 2025b: 2).

While the rights of copyright holders are recognised, problems remain. On the one hand, the training of GenAI models may still infringe copyright, depending on the facts. The limited transparency obligations of the providers of GPAI models under the AI Act (Recitals 104 and 107-108 and Art. 53(1)(d)) make it harder for copyright holders to understand whether their works have been used and to enforce their rights. The open wording 'appropriate manner' in Art. 4(3) of the DSM Directive might increase the perceived risk for copyright holders, dilute the enforcement of copyright and, in effect, reduce exposure to legal risk for the providers of AI models. On the other hand, there are fears that current regulation allowing copyright holders to opt out and refuse TDM on their content may lead to 'a fully copyright-licensed environment of machine learning' (Kretschmer et al. 2024: 111) especially if the threshold for the validity of opt-outs is low (EUIPO 2025: 73-74). This issue is explored in the following section.

2. Academics as users of GenAI tools in scientific research

Academic freedom must be protected regardless of whether academics are acting as researchers, educators, authors of works protected by copyright or users of works created by others. EU law also fosters the freedom to research when researchers use GenAI and TDM.

First, scientific research should generally be free of constraint in the EU (Charter of Fundamental Rights of the European Union (ECFR), Art. 13). Academic freedom, and freedom to research as one its core components, belongs to the fundamental values of both the European Research Area and the European Higher Education Area (Council of Europe 2012; Bologna Process 2020, 2024a, 2024b; Maassen et al. 2023).

Second, the interests of scientific research have, to some extent, been recognised in the AI Act, which does not apply to AI systems or AI models 'specifically developed and put into service for the sole purpose of scientific research and development' (Art. 2(6)).

Third, scientific research has also been addressed in the DSM Directive, which provides for a limited mandatory TDM exception for these purposes applying to 'reproductions and extractions made by research organisations and cultural heritage institutions in order to carry out, for the purposes of scientific research, text and data mining of works or other subject matter to which they have lawful access' (Art. 3(1)). 'Research organisations' and 'cultural heritage institutions' are qualified non-profit or public interest organisations such as universities (Art. 2, points (1) and (3)). A research organisation may rely on private partners to carry out technical activities (Recital 11; EUIPO 2025: 117-118).

Fourth, researchers can benefit from the GPAI code of practice. When researchers act as downstream users of existing models, they can mitigate their own risk by applying those of providers that have signed the GPAI code and are committed to using lawful training data and copyright safeguards. When researchers develop GPAI models themselves and place them on the market, they can be regarded as 'providers' (AI Act, Art. 3, point 3; European Commission 2025a: point 49), subject to the Act's copyright compliance obligations (Art. 53(1), point (c)). Such researchers can then voluntarily sign the code to demonstrate good faith compliance with the AI Act and to mitigate the risk of copyright infringements. Researchers that develop GPAI models may also benefit from provisions that foster the deployment of open-source and open-weight AI (AI Act, Recital 102 and Art. 52(2); The White House 2025: 4) without limiting copyright compliance obligations as such (European Commission 2025a: points 72-73).

However, problems remain. While the TDM exception for scientific research under the DSM Directive is not constrained by an opt-out mechanism (compare Art. 4(3)), it is constrained by the requirement of 'lawful access' and measures by rightsholders to ensure security and integrity (Art. 3(3)). Both constraints are connected and open to interpretation. This is likely to increase researchers' perceived exposure to legal risk (Kautio et al. 2025: 37). To reduce this, researchers may need to pay attention to the existence of copyright licences when using TDM (Kretschmer et al. 2024: 111). To protect academic freedom that, in essence, benefits the whole of society, legal risk should not be allocated to individual researchers that do not have the financial means to carry it. Higher education establishments, other research organisations and cultural heritage institutions should remain responsible for regulatory compliance and liable to the holders of copyright or related rights for the actions of their affiliated researchers under the principles of vicarious liability.

The limited organisational scope of the TDM exception for scientific research has a connection with academic freedom. There is no academic freedom without 'an institutional and organisational dimension, a link to an organisational structure being an essential prerequisite for teaching and research activities'.[2] Fundamentally, academic freedom and freedom to research is vested in the individual (UNESCO 1997: para. 20), reflecting its roots in human rights (United Nations 2020). Nevertheless, it seems open to what extent the TDM exception vests rights in the individual. To protect their members, trade unions should argue that the exception must be interpreted in

2. CJEU, Case C-66/18 *European Commission v Hungary*, para. 227.

the light of academic freedom (ECFR, Art. 13; CJEU Case C-66/18; Bologna Process 2020). The exception should vest rights in each individual researcher affiliated with one or more 'research organisations' or 'cultural heritage institutions'. It would not be acceptable to undermine academic freedom by leaving the personal scope of the exception and the circumstances under which it applies subject to organisational or management discretion.

The TDM exception for scientific research excludes actions other than TDM. While the open wording covers all TDM in scientific research (EUIPO 2025: 55), uncertainty should be reduced by naming the most usual permitted activities in authoritative sources. The DSM Directive only names 'the verification of research results' (Art. 3(2); EUIPO 2025: 94). Academics will also need to know whether exceptions apply to the sharing of mined materials for the purpose of collaboration (Fiil-Flynn et al. 2022) or other research purposes, and how GenAI outputs may generally be used (Kautio et al. 2025: 56-57). For example, the treatment of scientific peer review and joint research may depend on the Member State under the InfoSoc Directive (Art. 5(3)(a); DSM Directive, Recital 15).

The copyright protection of GenAI output raises fundamental questions (UK Government 2021, 2022). In Europe, the requirement of human intellectual effort excludes from copyright protection output produced without any human intervention (Hugenholtz and Quintais 2021: 1996).[3] However, prompting can be a human activity, as can be seen in jurisdictions elsewhere: while the non-protectability of such output seems to be the rule in the US,[4] it may be eligible for copyright protection in China (Frank and Schmid 2024).[5] Ultimately, algorithms do not need incentives; only humans do (Samuelson 1985; EUIPO 2025: 5). Fear of infringing rights in AI-generated content could be a deterrent to human creation (UK Government 2021) and the sharing of scientific knowledge. A conservative approach to copyright protection for GenAI output is in the interests of academics.

Finally, academics would benefit from a local innovation ecosystem with domestic GenAI firms. There are fears that regulatory overreach (Draghi 2025b: 79) and a full copyright-licensed TDM environment could have 'problematic effects for the structure of industry, innovation and scientific research' (Kretschmer et al. 2024: 111) since GenAI firms could relocate their model training operations to jurisdictions that offer a friendly regulatory framework (Fiil-Flynn et al. 2022; Peukert et al. 2025). This would also make it more difficult for researchers to complement scarce public funding with private sector sources (see e.g. Draghi 2025b: 191-192) and cooperate with the industry.

The rights of academics that use GenAI in scientific research should preferably be clarified to reduce their perceived risk.

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3. See also CJEU, Case C-145/10 *Painer*, paras. 87-88, 94, 99.
4. US Copyright Office, *re Zarya of the Dawn*, 21 February 2023.
5. Beijing Internet Court, *Lee v. Liu*, 27 November 2023.

3. Academics as users of GenAI tools in teaching

It is generally assumed that 'GenAI tools are changing the way teaching and learning content can be generated and provided' (UNESCO 2023: 36). Neither educators (Holmes and Tuomi 2022; UNESCO 2023: 26 and 30-33) nor the lecture hall (Holmes et al. 2022: 63) are likely to be replaced by technology in responsible, quality higher education. In contrast, the increased use of AI in education and other societal sectors will make it necessary to invest more in the training of educators (UNESCO 2021a: 35; UNESCO 2022, para. 104; UNESCO 2023: 26 and 28; AI Act, Recital 56, Arts. 5 and 9(5) and number 3 of Annex III). The use of GenAI for teaching and other educational purposes should be facilitated by IP law.

However, the wording of the limited mandatory TDM exception for the purposes of scientific research included in the DSM Directive does not extend to teaching. The DSM Directive distinguishes between research and education, between research organisations and education establishments, and between TDM for the purposes of scientific research and the digital use of works and other subject matter for the sole purpose of illustration for teaching (Arts. 3 and 5). In the latter case, the Directive is seeking to foster education (Art. 5(1)), which should seek to facilitate the use of GenAI in education (Art. 5(1)(a)) in the light of the systemic and internal coherence of EU law (ECFR, Art. 13; UNESCO 1997: paras. 28-29; InfoSoc Directive, Art. 5(3)(a); DSM Directive, Recital 84; AI Act, Recital 56; consolidated version of the Treaty on the Functioning of the European Union (TFEU) Art. 9).

The wording of the exception for the sole purpose of illustration for teaching can provide a legal basis. The 'digital use of works and other subject matter' implies that the exception is not limited to any particular teaching methods or technological tools in the education context. It should therefore cover the use of TDM and GenAI in teaching. To enable such use, educators should be able to use the technological tools provided by commercial undertakings (DSM Directive, Recital 11; EUIPO 2025: 117-118). The exception does not apply unless the use of such works 'is accompanied by the indication of the source, including the author's name, unless this turns out to be impossible'. While it is possible for educators to identify the chosen GenAI model, it is often not possible to identify the authors or copyright holders whose works have been used in the training of the model.

The copyright-related obligations under the AI Act and the GPAI code of practice may help educators indirectly. When the provider of a GPAI model has signed the code and chosen to follow it, the integration of the GPAI model into teaching will, in effect, pose a lower risk for educators. Moreover, the documentation shared under the AI Act (Art. 53(1), points (a), (c) and (d)) and the transparency chapter of the code can be useful in the teaching of AI.

As with academics engaged in scientific research, the rights of those that use GenAI in teaching should preferably be clarified.

4. Academics as guardians of scientific integrity and a scientific worldview

The use of GenAI for teaching and other educational purposes raises broad ethical concerns (see e.g. UNESCO 2022, paras. 101-111; Khalil and Er 2023; Sabzalieva and Valentini 2023: 10-11; UNESCO 2023: 14-17). The most fundamental problems relating to the deployment of GenAI in higher education and research are not limited to intellectual property but relate to integrity and scientific knowledge (European Research Council 2023: 12).

There are established quality standards in science guaranteeing the accuracy and objectivity of scientific results (UNESCO 2017, paras. 16 and 26). The use of GenAI tools in research should always be constrained by traditional research ethics and academic integrity (UNESCO 2022, paras. 108 and 110-111; Bologna Process 2024b: 2).

There is a risk, however, that the deployment of GenAI will pollute and dilute scientific knowledge. First, GenAI models are not designed to produce the scientific truth (see e.g. OpenAI). Large datasets based on texts scraped from the internet overrepresent hegemonic viewpoints and encode biases (Bender et al. 2021; Holmes 2023: 7). Moreover, the internet is increasingly polluted by false information. False information is generally easier to produce and distribute than the serious information intended to correct it (Vosoughi et al. 2018). Second, the increased use of GenAI in the production of content has created a loop that is undermining the scientific quality of content in the long term (UNESCO 2023: 16). Third, it is becoming 'increasingly challenging to determine the ownership and originality of the overwhelming amount of generated works' (UNESCO 2023: 36). The lack of traceability raises concerns about scientific integrity and whether original contributions to scientific knowledge are being appropriately credited and rewarded (UNESCO 2017, paras. 18(d) and 39). Fourth, since texts modelled on prior texts are faster and cheaper to produce, the increased use of GenAI may contribute to cementing the mainstream view, in the process marginalising potentially groundbreaking research (Coase 1988: 33; Holmes 2023: 7) that is slower and requires more significant investment (Bloom et al. 2020).

Trade unions need to address such research-related problems. When doing so, they should choose a holistic approach and focus on the quality of the content of academic work.

First, to prevent the contamination and dilution of scientific knowledge, trade unions should advocate a conservative approach to scientific integrity (see e.g. March 2007: 18; Bologna Process 2024b: 2-3) rather than promote mere human oversight or the presence of a human in the loop (European Commission 2019: section 2.2; Ponce Del Castillo 2024).

Second, trade unions should call for constructs that empower members to improve the scientific quality of their academic work and they should be paying attention to the structures in which the funding, recruitment and career advancement decisions influencing academics and researchers are embedded. In the era of GenAI, structures designed to increase quantitative productivity are less likely to improve the quality of academic work. There should, instead, be a greater focus on qualitative productivity, in which trade unions should reject overreliance on quantitative metrics and volume-based evaluation, but endorse evaluation based on the scientific quality of the content of academic work. Generally, they should be seeking to shift the focus of governments and institutional management to the creation of arrangements that facilitate more ambitious content. Compliance with the UNESCO Recommendation on science and scientific researchers (UNESCO 2017: 34) and the San Francisco Declaration on research assessment, commonly known as DORA, may be helpful first steps.

Third, trade unions should re-think their open science policy and focus on ways to empower members to improve the content of their academic work. In the light of the massive growth in scientific publishing channels (Nishikawa-Pacher 2022), publications (Kozlov 2023; Park et al. 2023) and tailor-made GenAI-produced content available to anybody, this should be more important than the manner of publication or the publication channel. Protection of the human rights on which academic freedom is based and of intellectual property are legitimate reasons to limit open science practices under international law (UNESCO 2021b: para. 8). Trade unions should defend each researcher's right to choose the manner of publication as an essential component of academic freedom (UNESCO 1997: para. 12) and their capacity to reserve rights under the DSM Directive (Art. 4(3)). While it is always necessary to balance different legal rights (Heck 1914; UNESCO 2017: paras. 18(d) and 21),[6] any restrictions placed on scientific researchers' right to publish or communicate results should be 'strictly minimized' (UNESCO 2017: para. 38(a)).

Re-thinking open science policy can be illustrated with the CoARA agreement on reforming research assessment (CoARA 2022). To empower members, trade unions should endorse the agreement to the extent that it asks to 'reward the originality of ideas, the professional research conduct, and results beyond the state-of-the-art' (CoARA 2022: 3). However, unions should reject the view that the manner of access to research publications is a question of the quality of the content. Readers' access to publications free of charge is one thing; the transparency of the scientific process is quite another (compare UNESCO 2017, Preamble, 'Also recognizing' (c)).

Conclusion

From a trade union perspective, intellectual property rights and policies relating to the deployment of GenAI are tools to defend the interests of members and to reach greater goals such as inclusive higher education, academic freedom and democracy. Trade unions should take a holistic perspective and protect academics as creators of works, users of works, researchers and educators. This requires protecting academics in each of their roles, which is not always an easy task since members may potentially have conflicting interests in their different positions. Trade unions should try to avoid trade-offs between their members' potentially conflicting interests: academic freedom

6. See also CJEU, Case C-401/19 *Poland*, para. 99.

and the intellectual property rights of academics benefit all. The costs of protecting the rights of academics in their different roles should be covered by the public funding of higher education.

It would bring benefits to clarify educators' and researchers' rights and duties in relation to the use of TDM and GenAI in higher education. Improved clarity can foster the deployment of GenAI. However, clarity by itself is not enough. The deployment of GenAI by educators and researchers relies on good industrial and regulatory policy.

The concentration of AI resources and development in global players outside the EU is a concern (European Research Council 2023: 10). While the 'United States is in a race to achieve global dominance' in AI (The White House 2025: 1), the risk for the EU is to be 'totally dependent on AI models designed and developed abroad' in the context of the EU's 'weak position in developing AI' (Draghi 2025b: 79). This is contributing to a serious innovation and productivity gap between the EU and the US (Draghi 2025a: 5). The EU should foster GenAI research and education by addressing all bottlenecks.

In higher education, some of the perceived bottlenecks relate to copyright and these are increasing the legal risk for academics. There will be no meaningful deployment of GenAI in higher education and research unless academics have the freedom to experiment in each of their roles. The exceptions under Arts. 3 and 5 of the DSM Directive and Art. 5(3)(a) of the InfoSoc Directive should be read as a whole and should ensure the parity of scientific research and teaching in the use of TDM and GenAI. In the light of the protection of academic freedom, they should cover the use of works for the purposes of scientific research and illustration for teaching by researchers and educators affiliated with an education establishment. It has become increasingly important to protect scientific knowledge and the copyright of academics wherein the strict protection of copyright should remain the default rule.

Again, however, this will not be enough by itself. A specific example is the General Data Protection Regulation (GDPR) that should address research-based education and clarify the legal basis of the use of AI under the responsibility of an education establishment (GDPR: Arts. 5-6; European Union 2025b: 79; EUIPO 2025: 33; Kautio et al. 2025: 29).

However, overreliance on AI or any other digital technology is unlikely to close the innovation gap (Kremer 1993), and the EU should thus consider other reforms. Contrary to its traditional piecemeal approach to regulation, the EU should take a more holistic perspective and focus on the fundamental structural problems that are hampering innovation. To foster this, the EU needs a higher education sector that is both decentralised and better integrated. The current fragmentation (Draghi 2025a: 16) and quality challenges (Draghi 2025b: 239-240, 231) of European higher education must be addressed by expanding the internal market (Letta 2024: 7; Draghi 2025a: 29-30) under the principle of effet utile.[7] Existing Treaty law does not categorically exclude

7. See e.g. CJEU, Case C-403/99, *Italy v Commission*, paras. 28 and 37; Cases C-562/21 *PPU* and C-563/21 *PPU, Openbaar Ministerie*, para. 95.

higher education and research from the internal market (TFEU, Arts. 57 and 107(1) v. Arts. 165(1) and 179).[8]

For the Council of Europe, the problems caused by the deployment of GenAI and digital technology in general (Mäntysaari 2025) indicate that a future recommendation (replacing Council of Europe 2012) should focus more on the specific contents of academic freedom and institutional autonomy. Such a recommendation should remain technology neutral, not least since academic freedom should not be compromised by technology hype. The default approach should be the protection of the intellectual property rights of academics and their right to choose publication channels (UNESCO 1997: para. 12).

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Abbreviations

AAUP	American Association of University Professors
AI	Artificial intelligence
DORA	San Francisco Declaration on research assessment
DSM	Digital single market
ECFR	Charter of Fundamental Rights of the European Union
ETUCE	European Trade Union Committee for Education
EU	European Union
EUIPO	European Union Intellectual Property Office
GenAI	Generative AI
GDPR	General Data Protection Regulation
GPAI	General-purpose AI
IP	Intellectual property
TDM	Text and data mining
TFEU	Treaty on the Functioning of the European Union
UK	United Kingdom
UNESCO	United Nations Educational, Scientific and Cultural Organization

Part 4
Working conditions considerations

Chapter 9
EdTech and the datafication of higher education

Janja Komljenovic

Introduction

The educational technology industry (EdTech) has been growing in scale and scope over the past decades, bringing new digital products, services and practices into the higher education and research (HER) sector (Selwyn et al. 2020; Decuypere et al. 2021; Williamson 2022). EdTech expansion has been supported by venture capital, expecting a return on investment and consequently bringing motivation for fast scaling and search for value in digital products and digital data collected by platforms (Komljenovic et al. 2023; Decuypere et al. 2024). This has significant consequences for universities more broadly and expressly for students and staff (Kerssens and Van Dijck 2022).

This contribution focuses on digital platforms in HER and the datafication of the sector, exploring the impact of both on academic labour. Datafication consists of collecting and processing data at all levels, from individual to institutional, national and beyond, with an impact on stakeholders' discursive and material practices (Jarke and Breiter 2019). While the current attention of education researchers and policymakers is extensively oriented towards generative artificial intelligence (AI), a focus on digital platforms and datafication is still necessary because of their consistent and steady development as well as the important influence they are having on education processes and practices.

1. EdTech industry traits

My research reveals three EdTech industry traits relevant to this contribution (Komljenovic et al. 2024). First, there has been a change in the business models and payment structure of technology products involving a decrease in perpetual licensing, with EdTech vendors increasingly offering digital products and services styled as software-as-a-service (SaaS) running on cloud infrastructure, for which universities pay subscription fees. New digital products typically come as SaaS; however, EdTech incumbents are also moving in this direction. For example, learning management systems previously came in the form of downloadable software running on university servers, but they are now being moved to cloud-based infrastructure. This matters because platforms offering SaaS collect and process user data to deliver the service. In addition, SaaS platforms push upgrades and updates automatically and continuously for all users at once.

SaaS is connected to the second trait, which is that digital services have become datafied. By this, I mean that various data operations have become integral to digital products. For example, a learning management system does not only allow the sharing of teaching material and asynchronous communication between students and tutors, as it did previously, but it now also offers data insights, such as learning analytics, recommendations for students and staff, automated flagging and other behavioural nudging and, more recently, AI-powered 'assistants' that staff can use to create courses (Komljenovic and Williamson 2024). Student and staff data is now routinely collected, processed and used in various computations to deliver these new data features which are integrated into the core product (Gourlay 2022; Czerniewicz and Feldman 2023).

Third, EdTech companies believe in the value of data and have engaged in various forms of data monetisation (Birch 2023). The most common way to monetise data in EdTech is via product development and improvement (Komljenovic et al. 2024). In the contemporary digitalised economy, technology companies' market capitalisations have a high value, mostly due to their collected data being treated as an asset (Birch et al. 2021). The economic value of the aggregated user data collected from staff and students can be observed in the case of acquisitions. An EdTech example is that of Instructure, the provider of the Canvas learning management system, which was acquired by the private equity firm Thoma Bravo for 2 billion dollars in 2020 (Young 2020). In the period leading up to the acquisition, the then chief executive stated that no one else in the world had such a comprehensive database on education experience and hence, no one else had the volume of data assets to develop algorithms and predictive models. In 2024, Instructure was acquired by KKR, a leading global investment firm, and Dragoneer, a growth-oriented investor, for 4.8 billion dollars (Instructure Holdings 2024).

These three industry traits contribute to the key processes that are relevant to the impact of platformisation on academic labour, to which I turn next.

2. Automatic updates

Digital platforms running as SaaS automatically roll out updates to their digital products. These include maintenance software updates but also entirely new features which are not necessarily welcomed by subscribing institutions and their constituents. For example, Turnitin rolled out an AI writing detection score in its plagiarism detection software, but it took decisive collective action from the sector for this feature to be made optional so that universities could switch it off if they wanted (Staton 2023). This shows the consequences of universities being locked in to a particular platform and its service and then made dependent on the processes that it introduces. The rationale is to keep expanding and scaling service provision (Shestakofsky 2025), but this is introducing new structural conditions for universities, staff and their practices.

Companies are continuously developing new analytics and other data-rich features to increase the value of their digital products (Pistor 2020). The most recent trend is including generative AI applications in different platforms with claims that these will help with efficiency and time saving. For example, generative AI has become part of learning management systems and allows the automatic production of course structure and other course materials. Before generative AI, various data features were integrated into products and made accessible via different tools, including dashboards displaying different analytics, and targeted at those responsible for leading specific processes or people although they did also offer a certain level of insight to individuals about themselves.

Software updates thus include a variety of features that have an impact on academic labour and that are not necessarily optional for universities as they can be organised as a core software functionality. These new features, whether wanted or not, affect academic freedom, staff and institutional agency and challenge the core of higher education (Komljenovic and Williamson 2024). They can be especially challenging for the sector if they come as part of larger enterprise-level technology provision, such as the Microsoft Office 365 suite. This is not specific to education, the underlying assumption being that analytical insights are equally relevant across sectors, but its application within HER can be at odds with high levels of professional autonomy and public values in higher education.

3. Work performance and surveillance

Digital platforms and the user data they collect facilitate the potential monitoring of staff and the calculation of various work-related performance analytics. These new metrics raise concerns about surveillance and accountability. All-encompassing platforms, such as Office 365, are able to collect and merge user data from various activities, including Teams activity, email communication, video calls, written documents, work patterns, times of activity and inactivity, and so on, giving administrators a detailed individual and group overview. However, the use of such data for staff monitoring is contestable: a report from the Netherlands recommends that public sector organisations 'establish policies to prevent Microsoft's analytics services from being used as employee monitoring systems', as this would have chilling effects (Privacy Company 2022).

The most common way EdTech companies have of increasing or keeping the value of their digital products is also to introduce ever more data features. My research points to an example of one EdTech startup that offers an e-reading platform and suggests student reading trends as a measure of staff performance, which seems to be of interest to university leaders in the USA. This is in contradiction to the beliefs and values of interviewees from universities elsewhere, who feel that, just because data exists, it does not have to be used (Komljenovic et al. 2024). This highlights the delicate balance between leveraging data for imagined benefit and encroaching on ethical practices.

4. Academic freedom and pedagogical autonomy

The output of EdTech's digital products affects the professional judgement of university educators, academic subjectivities and student-staff relations. They structure the teaching and learning process (Decuypere et al. 2021) and restrict educators' pedagogic autonomy (Kerssens and Van Dijck 2022). Agency and professional judgement are being challenged as aspects of teaching and learning processes become mediated by platforms and their algorithms. For example, plagiarism detection software assumes student dishonesty, thus intervening in the student-educator relationship, while at the same time commodifying student assignments (McKenna 2022).

Digitalisation and datafication in higher education are bringing new tasks and expectations and reshaping academic work (Castañeda and Selwyn 2018). Platform companies promise efficiency; however, university workers, including academic and professional staff, are ending up with more work around data collection, processing and management (Komljenovic et al. 2024; Woelert et al. 2025a, 2025b).

5. The bottom line

The way the EdTech industry operates in HER is subject to a complex relationship between EdTech companies, universities, end users and regulators. EdTech operates under conditions influenced by a complex interplay between technological, economic and legal factors. Students and university staff are governed not only by sectoral laws and regulations but also by digital governance regimes aimed at protecting people as they engage with digital platforms more generally, most notably via data privacy regulation. Students and staff are thus also ‘digital users’ (Noteboom 2025). However, data privacy legislation is not necessarily compatible with labour law in governing privacy and the monitoring of work (Molè 2025). In addition, as end users, staff and students need to accept the terms of service of specific platforms over which they have no choice and which might limit their freedoms and rights. Staff and student rights, as they become digital users, thus change from a traditional academic understanding of academic freedom and autonomy, and of particular roles as university constituents, to being governed now also by contract and property law via terms of service and privacy policies.

EdTech and data operations are not transparent in their design, function and impact (Brown and Klein 2020). Therefore, universities as well as technology companies working with universities must provide greater transparency on technology and the data processes and practices that are being applied in HER. In addition, data becomes valuable when aggregated and processed on the basis of making comparisons between people. Hence, one person’s actions influence others. For this reason, EdTech products need new forms of democratic and relational governance, such as data commons or data trusts (Viljoen 2021).

Finally, the key organisations with the power to negotiate the conditions of platform operations are universities – alone and collectively. Thus, it matters what kind of policies they develop internally for EdTech procurement and use, and for user data operations beyond data privacy. However, not all universities have yet advanced this thinking and organising of their operations in that they are not broadly including their staff and students in strategy development and technological decision-making (Williamson 2024). This needs to change in the future as staff and students should be included in EdTech decision-making at all levels.

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Abbreviations

AI	Artificial intelligence
EdTech	Educational technology (industry)
HER	Higher education and research
Saas	Software-as-a-service

Chapter 10
Anticipating the cognitive impact of extended reality: beyond student perspectives

Emmie Hine

Introduction

Extended reality (XR), an umbrella term for immersive technologies including virtual reality (VR), augmented reality (AR) and mixed reality (MR) (Milgram and Kishino 1994; Skarbez et al. 2021; Bernardo 2025), is poised to transform higher education. Yet discussions often fixate on student experiences, overlooking the cognitive impacts on the educators and researchers who design and use these tools. This chapter broadens the view beyond students, examining how XR might affect the ways academics, educators and researchers work, both inside and outside the classroom. By *cognitive impacts*, I refer not only to the direct psychological effects on attention, memory or perception but also to the broader social and ethical consequences that influence how people think, learn and collaborate. In other words, XR's impact on cognition encompasses everything from individual mental health and workload to collective issues like bias, inclusion, privacy and academic freedom. Reigeluth (this volume) offers a complementary perspective in asking just how far the automation of learning and evaluation should go and what kinds of educational goals universities may wish to preserve when they introduce these tools.

The goal of this chapter is to anticipate both the opportunities and challenges XR presents for higher education professionals and to suggest strategies to maximise the benefits while mitigating the risks. I situate XR within the wider 'automated classroom' trend (Stolurow and Davis 1963; Hof 2023) – the 'persistent assumption that learning… can be made more efficient with technical teaching aids' (Hof 2023). This includes the convergence of XR with artificial intelligence (AI) and data analytics in education. Indeed, AI-powered virtual agents and analytics often accompany XR environments, enabling adaptive learning but also raising new privacy and bias concerns. Following this introduction, I separately consider XR's impacts on academics' work in the office (including research and administrative work) and then within the learning environment (primarily comprising teaching). Each section highlights concrete examples across disciplines, balancing positive innovations against potential cognitive and socio-ethical downsides. I then conclude with actionable insights for policymakers and academic leaders on integrating XR responsibly.

1. XR in the office: new horizons and new cautions

One of the most exciting prospects for XR in academia is the opening of new research avenues across diverse fields. XR's capacity to create highly realistic, controllable simulations offers researchers novel experimental possibilities that would be difficult or impossible in physical settings. For example, in psychology and psychiatry, VR has been used to treat phobias and post-traumatic stress by safely exposing patients to triggering scenarios, showing promising results in therapeutic outcomes (Park et al. 2019). In architectural and engineering research, XR allows designers and participants to experience building prototypes or complex machinery at true scale before they exist, potentially improving spatial understanding and design feedback (Darwish et al. 2023). Thanks to the realism created by VR's sense of presence, immersion and interactivity (Mütterlein 2018), researchers can conduct experiments with participants in lifelike virtual environments, potentially more efficiently and at lower cost than in-presence. Early evidence suggests that such experiments can maintain high construct validity (i.e. accurately model real-world conditions) while offering easier repeatability and scaling (Gavazzi et al. 2011; Feng et al. 2019), although one study notes that at-home participants had to be removed more often than in-person ones (an issue shared with other forms of remote research) (Ratcliffe and Tokarchuk 2022). In short, XR is emerging as a powerful scholarly tool – not only as an object of study (research on XR itself) but as a medium for discovery in fields as varied as behavioural science, geography and environmental science.

Alongside enthusiasm for XR's research potential, researchers must exercise caution to ensure that virtual studies are epistemologically sound. One key consideration is the simulation caveat: because experiments in VR are simulations, they may not capture the full unpredictability of the physical world. Just as AI models trained on synthetic or limited data can miss real-world nuances, an XR-based study might inadvertently oversimplify complex phenomena, including through the absence of equivalent haptic feedback (Chawla et al. 2022). Researchers must therefore carefully validate that the results obtained in a virtual environment would be likely to hold in physical settings. Methodological rigour – for example, comparing VR and in-person trial outcomes – is needed before generalising findings.

Another concern is ensuring XR research does not introduce new biases or exclusivity. Design bias in XR hardware and content can skew research samples if not addressed. For instance, some VR headsets have historically been optimised for adult male bodies, leading to discomfort or the 'cybersickness' (essentially VR-induced motion sickness) that disproportionately affects women (Stanney et al. 2020; Kelly et al. 2023); equipment and software must accommodate a diverse population rather than a one-size-fits-all user. Similarly, certain VR designs overlook cultural and physical diversity: a device that does not accommodate varied hair textures or head coverings can effectively exclude participants from certain ethnic backgrounds (Mboya 2020); while many devices are not accessible to people with physical disabilities (Hine 2025). As one study bluntly puts it, current XR technology 'favors the young White male population without physical or psychological disabilities' by design (Stendal and Bernabe 2024). This is a stark reminder that, if researchers only recruit the most comfortable or obvious users of XR, their findings will lack generality and may perpetuate bias. To counter this, research teams should proactively ensure accessibility. Where specific groups (such as people with visual impairments or mobility limitations) cannot directly use the XR setup, researchers might develop alternative interfaces or complementary methods so these voices are not completely left out. In short, maintaining inclusivity in XR research is both an ethical imperative and essential for robust data. Researchers venturing into XR should do so with excitement tempered by methodological caution.

When using XR for other work outside teaching, there are some adverse effects of long-duration VR use that could affect academics.[1] For instance, prolonged wear of VR headsets or AR 'smart glasses' has been linked to symptoms of dissociation – a sort of detachment from reality or difficulty reintegrating to the physical world after being immersed (Aardema et al. 2010) – as well as addiction (Barreda-Ángeles and Hartmann 2022). Though few may anticipate getting addicted to their virtual office, we should be wary of the potential psychological effects of long-duration VR use. More common are issues of heightened anxiety or discomfort; one experiment showed that doing identical work tasks in VR (compared to doing so in a physical office) significantly increased people's perceived workload and anxiety levels (Fernández-Batanero et al. 2021). Additionally, 'passthrough' MR devices – which show physical surroundings on a screen while overlaying virtual elements – can make users feel less connected to the actual people around them (Bailenson et al. 2024), including colleagues. Finally, as discussed, many XR devices still cause cybersickness, with disproportionate impacts on specific groups. A researcher who has to worry about nausea each time they use XR will hardly be enthusiastic about incorporating it daily. There are both software and hardware interventions, as well as strategies for users, that can mitigate the impacts of cybersickness (Biswas et al. 2024), making it likely that this will become less common as technology advances. Yet, counting on technology to improve naturally is not a sufficient solution; conscious efforts must be made to design educator-friendly XR equipment and to encourage healthy limits on usage (much like screen time recommendations for digital devices).

2. XR in teaching and learning: promise and pressure

In the realm of teaching and learning, XR has generated considerable optimism about its potential to enhance education. For educators, XR offers new ways to engage students and enrich the curriculum. For example, a biology lecturer can take students on a virtual field trip inside a human cell, navigating three-dimensional organelles at microscopic scale (de Jong et al. 2025) – a dramatically different experience from static textbook diagrams. A history professor might recreate an ancient Roman forum in VR (Solly 2018), letting students wander and interact with historical characters, thus bringing history to life. Such applications display the advantages of immersive learning. As a result, XR can boost students' motivation and engagement by making learning more experiential and interactive, and also by improving learners' skills, compared to traditional methods (Zhang et al. 2024). XR can also facilitate personalised learning when combined with AI: imagine an AI-driven virtual tutor in an AR headset that provides real-time feedback as a student works through a problem set, or adaptive VR scenarios that adjust difficulty based on the learner's progress. Though still largely theoretical, the goal of integrating AI with immersive narratives is improved memorability and motivation, achieved by placing students at the centre of interactive

1. Many of these could also affect educators in that environment but, to avoid the repetition, they are discussed here.

stories rather than being passive recipients of information (Jalili 2024). These cognitive benefits for students are key reasons for educators to explore the use of XR; though students are the ones being directly influenced by the lesson, the potential for pedagogy to be transformed also has an impact on educators, and in many ways.

With new technologies comes enthusiasm, but XR has potential negative psychological and cognitive effects that educators themselves will bear as they are typically the ones managing technology in practice. Teaching with XR can introduce new cognitive loads and stresses on educators. Beyond the headset-induced effects discussed above, perhaps the more significant cognitive impact of XR (or any new tech) in teaching is the extra burden on educators to integrate it into their pedagogy and manage any fallout – something which research has shown is linked to increased educator stress and anxiety (Fernández-Batanero et al. 2021). This has played out in the public arena as chatbots based on large language models (LLMs), like ChatGPT, have forced many to rethink their pedagogy on the fly (Roose 2023). Educators, from primary school to college professors, will have to deal with the disruptive impacts of new technology and, on top, its additions to their already-significant cognitive burden. They must rapidly learn the tool, plan lessons around it, troubleshoot technical issues and handle student reactions – all on top of their regular duties. XR could bring its own versions of such disruption; the potentially thrilling teaching methods outlined above must be developed and incorporated into lesson plans, while virtual environments could enable new forms of misbehaviour or see some students respond poorly. Educators thus face a dual challenge: harnessing XR's benefits for learning while mitigating misuses and any student wellbeing issues that arise. This can only add to their cognitive load, at a time when educator burnout is already a concern (Walker 2025).

To avoid overburdening educators, any introduction of XR in teaching should be accompanied by strong institutional support. This includes professional development and training: educators need time and resources to become comfortable with XR tools before being asked to use them in practice. Studies on VR adoption emphasise that ongoing training and technical support are essential to build educators' confidence and skills in using these tools effectively (Carpenter et al. 2023). Peers and experts can share best practice, like how to manage a learning environment in which half the students are in headsets or how to assist a student who panics in a VR simulation.

It must also be accompanied by policy support: clear guidelines on appropriate use (e.g. codes of conduct for virtual learning environments; measures against cheating or harassment in VR) so that educators are not alone in establishing the ground rules. Crucially, universities should not assume that educators will single-handedly handle any student psychological impacts from XR. If a student experiences distress or negative effects from an XR activity (for example, vertigo or emotional upset from an intense simulation), there should be counsellors or support services available – the responsibility should not fall solely on the educator.

Additionally, to address equity, institutions must consider access issues from the start. XR devices can be expensive; if only some students can afford their own or if devices are scarce, educators may have to deal directly with a digital divide. Ensuring that all students have the necessary equipment (via institution-provided devices or subsidies for low-income students) is important both for fairness and for minimising the burden on educators. Likewise, content should be vetted for cultural bias and diversity – educational XR experiences ought to represent a range of genders, ethnicities and perspectives to be inclusive, rather than all avatars or examples defaulting to a particular demographic; historically, avatars have not been inclusive (Hine 2025).

By proactively addressing these factors – training, policies, student support and equitable access – education institutions can significantly reduce the cognitive and administrative burden on educators and allow them to focus on teaching students, with XR as an augmenting tool.

One final issue that must be discussed is that of data privacy and academic freedom. A defining feature of XR platforms is that they exhaustively track user behaviour to create the immersive experience: motion sensors record how users move their head and hands; eye-tracking cameras note where they look; microphones capture their voice; and so on. This means if universities start using XR for work and administration (whether for teaching, research or meetings), they will be capable of collecting unprecedented amounts of biometric and behavioural data on staff and students (Hine et al. 2024). Even if the institution itself doesn't intend to surveil, the software and hardware (often provided by private tech vendors) can still be recording this data. This raises obvious privacy questions. Who owns and controls the data? How will it be used, and for how long? There have already been early warning signs. For example, in 2024, the University of Michigan faced an outcry when it was discovered that a contractor had licensed a dataset of recordings and student work to train AI models – all without the clear consent of those recorded (Cox 2024). The recordings dated back to the 1990s, so participants could not have known their interactions would be repurposed decades later for commercial AI development. Although that dataset did not involve XR, it highlights a potentially slippery slope: today it is video recordings and papers; tomorrow it could be full 3D behavioural logs of everyone in a lecture hall. XR data is immensely rich – not just what a person said or wrote, but how they moved and to whom they paid attention; even their physiological responses in some cases. Though individual datapoints are not identifiable, they can be once aggregated; some data aggregations can provide information on personal characteristics and health conditions (Hine et al. 2024). Under Regulation (EU) 2016/679 (GDPR; General Data Protection Regulation), much of this is likely to qualify as special category data because it reveals sensitive biometric or health information. European universities that adopt XR therefore become data controllers with all the compliance obligations therein.

Regardless of legal compliance, the thought of employers or school administrators having access to such granular data on educators' and students' daily activities may be unsettling for academics and educators. At best, it could be used for benign analytics; at worst, it opens the door to micromanagement and surveillance. Many workplaces already use productivity tracking software on employees' computers, but XR could take it further – monitoring not only keystrokes or websites accessed, but an educator's gaze and gestures in a virtual learning environment. Moreover, research has shown how VR allows for the gathering of detailed information about group dynamics – such as who is interacting with whom, how groups are relating to each other and how students are reacting to others (Stanford HAI 2022). Proponents of data analytics in education might argue that, if used ethically, such detailed data could help improve teaching and working environments. For instance, analysis of VR classroom logs may show that certain students are consistently less engaged or never interact with particular classmates. This might help identify participation gaps or social exclusion that could then be addressed, promoting a more inclusive environment. Indeed, one suggested use is to detect and correct bias. For instance, an XR system could potentially reveal if a lecturer unintentionally calls on male students more often than female ones, since studies have found men speak up to 1.6 times more in traditional learning environments (Lee and Mccabe 2020). By surfacing such patterns, universities could offer feedback or training, nudging educators towards more equitable teaching practices.

However, these upsides come with significant caveats. First, the reliability of such behavioural metrics is questionable. Human interactions are complex and context-dependent; reducing them to quantitative metrics (like 'speaking time' or 'eye contact frequency') could potentially mislead. For example, an educator's reasons for calling on particular students and not calling on others might not be bias at all but based on situations that raw data cannot capture – perhaps a particular student has a propensity to disrupt the class when called on. Relying on automated data analysis without context could unfairly malign educators or students. Second, and more fundamentally, constant monitoring can produce a chilling effect on academic freedom and trust. If educators know that every movement and micro-interaction in an XR environment could be scrutinised by their boss (or by an algorithm), they may become self-conscious and hesitant in their teaching. Surveillance anxiety can cause people to self-censor – a phenomenon already documented in online spaces under surveillance (Penney 2016). Translated to academia, one could imagine a professor avoiding controversial research topics or class discussions for fear that an automated system might flag them as problematic. Would students be comfortable bringing up certain topics in a VR classroom if they knew their institution could potentially be monitoring whatever they said (or even selling it to the highest bidder)? Would professors? What research ideas would not be explored out of surveillance concerns? The free and open exploration of ideas – the cornerstone of higher education – could be inadvertently stifled.

Academic work has traditionally enjoyed autonomy and privacy. XR and AI technologies challenge this by making all work visible and recordable. If a university administration wanted, it could conceivably require educators to use an official VR lecture platform that logs all interactions. Even if not used punitively, the mere perception of surveillance can erode trust. Moreover, there are scenarios where XR data might be misused. For example, could a university use subtle behavioural data (collected via faculty use of AR glasses) in performance evaluation? This might seem far-fetched, but such technologies are already feasible. Notably, the AI Act passed by the European Union (EU) bans emotion recognition in educational and workplace settings, deeming it too invasive and unreliable (Art. 5), but this does not cover all XR-related data mining.[2] This is a proactive stance to protect privacy, but such regulations are not universal. In regions

2. Many AI systems used in education and workplace settings are considered high-risk (Annex III).

without similar protections, institutions or vendors might experiment with analysing XR-derived data on attention, emotion or engagement, to the potential detriment of educators.

It is important to note that these data concerns are not unique to XR – they echo issues with other education technologies and AI tools. Many faculty staff and students are indeed already voluntarily feeding academic data, such as papers and lecture slides, into AI services like ChatGPT.[3] In doing so, they may be bypassing any university oversight, while exposing themselves to third-party data mining. Similarly, if an academic uses a commercial VR platform (say, a popular metaverse app) to hold office hours, the platform provider may use that data for analysis and profit. Universities and policymakers should thus extend their digital governance frameworks to XR, clearly communicating to educators and students the risks of using external XR/AI tools with institutional data. Where possible, they should also be negotiating contracts with vendors that protect user data and intellectual property. The principle of informed consent is all the more critical in the XR era – people should know if and how they are being monitored and they should have the ability to opt out or at least appeal unfair uses of their data.

Conclusion

Extended reality is arriving in education, bringing profound potential along with cognitive and ethical complexities. This chapter has explored XR's anticipated cognitive impacts beyond the student perspective, assessing impacts for educators and researchers both in the office and in the lecture hall. Overall, the outlook is mixed but hopeful: XR can greatly enhance how we explore knowledge and convey it to learners, yet it also poses risks from psychological strain to surveillance creep. It is crucial that academic institutions and policymakers act proactively so that XR's rollout strengthens education rather than unintentionally undermines it.

On the positive side, XR opens up exciting new horizons for research and pedagogy. Scholars can run experiments and visualise data in ways never before possible, and educators can immerse students in rich learning experiences that boost engagement and understanding. XR, especially in combination with AI, could personalise education and make learning more accessible. Moreover, XR can break down physical barriers, connecting people across distances in shared virtual spaces, with benefits for collaboration and inclusion (consider a disabled student who can attend a virtual lab that is easier to navigate than a physical one).

On the negative side, the cognitive tolls and ethical pitfalls must be acknowledged. These include the health and psychological effects, the increased cognitive load on educators and the risk of widening inequalities if technology design and access are not made inclusive. Perhaps most broadly, there is a danger that rushing into XR without safeguards could erode trust – e.g. if surveillance and data misuse are allowed, or if educators feel overwhelmed and unsupported in the face of constant technological change.

3. I am grateful to an anonymous peer reviewer for this comment.

To ensure XR's promise outweighs its downfalls, I propose the following key steps for institutions and policymakers:

1. Invest in training and support. Faculty and other staff need structured training programmes to learn XR tools and pedagogies. This builds confidence and competence, reducing cognitive overload. Additionally, ongoing technical support (e.g. an 'XR helpdesk') should be provided so that educators are not left to troubleshoot alone during a class or project.

2. Prioritise inclusive design and access. Universities should work with manufacturers to ensure devices and software accommodate diverse body types, abilities and cultural contexts. This ranges from adjustable hardware (to fit different faces and heads) to content that is culturally sensitive and available in multiple languages. Importantly, the digital divide must be addressed by budgeting for class sets of XR equipment or subsidies so that *all* students and staff who need XR access can have it – avoiding a scenario where only well-funded departments or individuals benefit from the technology.

3. Set clear ethical guidelines for data and privacy. Before adopting XR campus-wide, policies need to be established on what data is collected and how it is used, based both on GDPR/AI Act compliance obligations and ethical best practice. Intrusive monitoring (such as secretly tracking gaze or emotions for punitive purposes) should be prohibited, while transparency and consent must be required for any data-driven initiatives. Whenever possible, data from XR should be anonymised and used only to benefit users (e.g. improving a system) rather than to police them.

4. Protect academic freedom in the XR era. Faculty representatives should be included in decisions about XR platform adoption and analytics, while governance mechanisms (such as committees or ethics boards) should be introduced to review any surveillance-related proposals. Faculty staff and students should be able to use XR for creative and controversial ideas on the basis of an assurance that their every move is not being monitored. In practical terms, this might mean keeping certain spaces or sessions entirely unrecorded, or giving users the ability to access and delete their personal interaction data.

5. Encourage interdisciplinary research on XR's impacts. There is still much we do not know about XR's long-term cognitive effects. Funding should be directed to studying these questions in diverse fields, so policy can be guided by evidence. Likewise, end-users should be involved in pilot projects and their qualitative feedback gathered systematically. This continuous research and feedback loop will help identify unforeseen issues early and develop effective interventions.

XR has the potential to be a transformative tool for higher education, expanding the frontiers of research and enriching teaching and learning. If implemented thoughtfully, XR could help produce a generation of scholars and students who are more engaged, skilled and globally connected. With enterprise applications increasing (Data Horizon Research 2025), the technology's immersive power is likely to influence how the future workforce will operate, so academia must be at the forefront of shaping that transformation responsibly. By anticipating the cognitive impacts and addressing them, universities can ensure that the virtual revolution uplifts our education mission rather than distracts from it.

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Abbreviations

AI	Artificial intelligence
AR	Augmented reality
EU	European Union
GDPR	General Data Protection Regulation
LLM	Large language model
MR	Mixed reality
VR	Virtual reality
XR	Extended reality

Chapter 11
Strategies for organising against AI in higher education

Robert Ovetz and Lindsay Weinberg

Introduction[1]

Higher education administrators, tech industry insiders, education entrepreneurs and policymakers are currently engaged in a pressure campaign to make the transformation of higher education by artificial intelligence (AI) appear inevitable (Williamson 2024). Despite their efforts to impose it on academic workers, the future of AI in higher education is not a foregone conclusion. Academic workers can organise to contest, refuse and ban extractive AI, by which term we mean the use of technologies marketed as AI to impose hierarchies of labour and knowledge that ultimately serve to exploit and subordinate workers around the globe (Pasquinelli 2023).[2]

OpenAI's ChatGPT, released in November 2022, is only one example of how AI is being integrated into higher education to automate some aspects of teaching as part of a strategy to weaken academic unions and strengthen Big Tech's hold on higher education and research (HER). An AI avatar, developed in partnership with VictoryXR and trained with a professor's lectures and course notes, is being used at Morehouse College, which has received substantial funding from Facebook's parent company, Meta (Coffey 2024b; Walters 2024). Arizona State University has partnered with OpenAI to use ChatGPT as tutors in its large first-year composition class (Warner 2024). San José State University, home to one of the authors, has announced a public-private partnership to expand the use of AI for research and workforce development (SJSU 2024). Major academic publishers are partnering with Big Tech companies, including Microsoft, to provide academic content for training large language models without authors' consent (Dutton 2024). Most obviously, the Dean of Arts and Sciences at Boston University proposed the use of generative AI (GenAI) for assignment feedback and discussion facilitation to break a strike by teaching assistants (Tran 2024). Universities are also using predictive analytics to monitor student and faculty performance in ways that intensify inequality and exploitation, and computer vision – a field within artificial intelligence – to install

1. This chapter is based on the authors' collaborative research for a book and a forthcoming chapter in Holmes W. and Pelletier C. (eds.), Handbook of critical studies of artificial intelligence and education, Edward Elgar Publishing.
2. In practice, AI does not refer to a coherent set of technologies but is frequently used to sell a range of task automation tools encompassing decision-making, classification, recommendations, transcription/translation, and text and image generation (Hanna and Bender 2025). While AI research as a field goes back at least 70 years to Cold War efforts to guide military and administrative systems, the recent popularisation of the term 'AI' to sell these tools occurred in the 2010s due to advances in machine learning. This has subsequently led to an influx of speculative venture capital investments and Big Tech monopolies over the vast computational infrastructures required for more complex model training and development.

repressive regimes of campus surveillance against activists and academic workers (Weinberg 2024).

Despite these developments, the large academic unions in the United States (US) are not organising against the top-down integration of AI tools on their campuses but, rather, are collaborating in their use. Other unions are leading the struggle against AI. The Writers Guild of America (WGA) and the Screen Actors Guild-American Federation of Television and Radio Artists (SAG-AFTRA) have struck to demand better wages, job security and veto power over working with GenAI (Scherer 2024). Academic workers can adopt and adapt the lessons from these unions' fights.

This chapter analyses the strategic implications of AI in academic labour organising. Section 1 provides a brief overview of how the strategies of the large US academic unions have contrasted with AI-related organising tactics in other sectors. Section 2 describes the results of an analysis of existing collective agreement (CLA) language on AI in the US and the European Union (EU), revealing that the primary union strategy is to collaborate on the introduction and use of AI in the workplace. Section 3 then argues the urgency of academic workers collectively refusing extractive AI and how the methods of workers' inquiry help to identify appropriate tactics, strategies and objectives for doing so. Academic workers, including faculty and support staff, and students can protect themselves against extractive AI by learning from union organisers across sectors and by acting in solidarity with precarious workers across the AI supply chain.

1. Learning from other strikes

Rather than organise against AI, the two largest US academic unions have embraced its 'promise', leaving faculty and other staff, and students, on their own to self-organise. Despite widespread reports projecting the loss of hundreds of millions of jobs globally in the next few years (Ovetz 2023b), the American Federation of Labor-Congress of Industrial Organizations (AFL-CIO), the American Federation of Teachers (AFT) and the National Education Association (NEA) are making peace with AI and none are proposing to organise against it (AFT 2024a; Coffey 2024a; McMurtrie 2024; NEA 2024a). In fact, the AFL-CIO is promising to collaborate with Microsoft on implementing AI generally in the workplace (AFL-CIO 2023; Scheiber 2023; Ovetz 2024a).

This is in contrast with the strikes and strike threats by the WGA, SAG-AFTRA, UPS Teamsters, Culinary Workers Union and the International Longshoremen's Association over the use of AI to automate or surveil (Ovetz 2023a; Lutz 2024). The two Hollywood strikes by the WGA and SAG-AFTRA were primarily about GenAI and, up to now, they are the first two post-ChatGPT strikes that have resulted in any form of worker control over it.

Academic workers can, however, learn from these recent strikes and strike threats and draw lessons from organisers on how to bargain over AI in the workplace. There are two possible strategies: collaborate with its use in order to redistribute the supposed benefits of AI implementation; or organise collectively to refuse and ban extractive AI tools from academic workers' campuses.

2. The collaborative strategy: notification, voice and participation

US academic unions are openly collaborating with AI tech companies. NEA's 2024 AI policy statement paves the way for sanctioning and integrating AI into universities by emphasising participation in the design of AI tools for education and equitable access to AI in schools (NEA 2024b: 6). The AFT is even funding an AI Educator Brain and working with Microsoft to pitch AI to its members (AFT 2024b).

The NEA and AFT approach is not unique – although other specific examples remain rare. The authors have analysed existing collective agreements in the US and EU and find that, as of February 2025, the number of agreements with language concerning AI or algorithmic management is still very small while fewer still are in higher education. A survey for UNI Global Union, the European labour federation, conducted between April and September 2023, found only 31 unions with any reference to AI in their agreements (Brunnerová et al. 2024). There are only two comprehensive sources for union language on AI: the international labour federation Public Services International database of model AI collective agreements, drawing mostly on US and European union sources; and the UC Berkeley Labor Center's list of CLA language related to AI and algorithmic management in the US (Kresge 2020).

Even though the number of agreements is small, the primary union strategy concerning AI is to collaborate in its introduction. This approach seeks to mandate participation in decisions concerning its use in order to moderate its impact, which has the effect of sanctioning it within the workplace. This strategy of acceptance assumes that AI can benefit workers if they have notification of its introduction, voice about its use and participation in making new work rules – what we term 'NVP'. The underlying assumption of NVP is that an employer's use of AI can be bargained to create new contractual 'rights' for workers. These include protections against surveillance and discrimination in hiring, evaluation and promotion decisions; consultation over its use in the workplace; the potential for reviewing and challenging the data; 'royalties' on productivity increases; compensation for job losses; and the right to disconnect. This approach is reflected in the EU's 2024 Artificial Intelligence Act as well as in the policy positions issued by the previous Biden administration (Abruzzo 2022; Goldman 2022; OSTP 2023; Kelley 2024).

The NVP strategy assumes that workers using AI can share in the higher productivity and profits: to trade collaboration for higher pay, reduced work hours, retraining, a share of higher profits and new AI-related job categories in the bargaining unit. The underlying logic is that, since AI will be introduced into work, workers should share the purported benefits from using it.

However, there are many examples in which a strategy of collaboration with the introduction of automation technology has been a losing strategy over the long term. In the US, there are two that are well known (Fairley 1961; Ovetz 2024b): the 1950 Treaty of Detroit between the United Auto Workers and the big three carmakers; and the International Longshore and Warehouse Union and Pacific Maritime Association's

1960 Mechanization and Modernization Agreement. These agreements traded new technology and increased productivity for NVP and higher wages and job security. Over the past sixty years, the result has been widespread automation and a decline in the number of workers and union power in both industries. As workers become more productive, they are at the same time becoming deskilled, while the overall workforce is shrinking as a result of redundancies, attrition, retirements and turnover despite retraining. This leaves the shop increasingly automated with far fewer human workers and weakened unions, as can be seen in most auto plants and in the ports (Nolan 2024; Rahmati 2024). There are lessons from these past struggles over the introduction of automation for those fighting extractive AI in academia.

The collaboration strategy frames AI as a rights or share of productivity issue rather than a management labour control strategy. Because the workplace is an authoritarian sphere, constitutional rights do not apply unless they are written down in a collective agreement, which cannot be obtained by bargaining and the pursuit of grievances alone (Anderson 2017). Workers have no rights other than those that they obtain through their own organised power in the workplace.

The NVP strategy allows workers to be consulted but never to control whether and why AI is being used (CWA 2023) because it accepts the principle of 'management acts, workers grieve' inherent in the collective bargaining process. By framing the issue of AI as a matter of bargaining and not who wields power over work, it leaves management fully in control. Workers' only recourse is to respond once introductions have been made and to bargain over the effects. This is amplified by 'management rights clauses' in most US CLAs that allow management control over anything not allowed or prohibited in the agreement. US labour law restricts bargaining to wages, hours and working conditions, while preventing workers from democratically controlling their work (Ovetz and Van Meter 2023).

By using the NVP strategy, unions risk aligning with employers against their own members and all non-union education workers, as AFT and NEA are doing. Their approach misses that AI is often a tool for rationalising and deskilling academic labour to control, automate and outsource academic work. AI is being strategically used to fragment our labour and intensify demands for productivity and worker self-discipline, weakening the power of organised workers (CLF 2024). AI is being presented as an individualised 'solution' to overwork that divides academic workers over whether to resist or coopt it. While academic workers remain divided, the major unions are collaborating with tech companies in a self-defeating effort to influence AI.

The collaborative strategy not only disempowers workers by leaving control over AI to management, but it also overlooks the issues of economic and environmental exploitation woven into the AI supply chain (Dencik et al. 2024: 24). Shifting from such a strategy to organising for worker power requires understanding extractive AI as a labour control strategy. In this sense, AI is a tool to increase productivity by rationalising labour to extend management's control, weaken workers' control, decompose workers' power to organise and reduce dependence on secure human workers.

3. Organising collective refusal and banning AI

Because of the AFT and NEA's collaborative strategy, there is little organised opposition to AI in HER. Examples such as the October 2024 rank-and-file effort to persuade the member assembly of the California Faculty Association (CFA) to vote for academic workers' control over AI are rare (CFA 2024a). In the UK and Scotland, the University and College Union (UCU) has been increasingly focusing on the threat of algorithmic management and AI since at least 2020 (Williamson 2020). Organising is urgently needed in the political context of the US federal government making significant efforts to deter state-level AI regulation via a 10-year moratorium (Huckins 2025) and where universities and the major academic unions have been keen to partner with Big Tech despite the social, environmental and pedagogical harms of their products (Williamson 2024). A strategy for academic workers to refuse AI can, however, be based on a workers' inquiry with the aim of developing new tactics and approaches to organising along the entire global AI supply chain.

Using AI to automate, control and deskill academic teaching labour often requires an immense number of globally dispersed workers – many of them in the Global South – to assemble and annotate the data required to train and correct the GenAI models being pushed on academic workers. A workers' inquiry could seek to connect campus workers with the exploitation of these low waged and precarious data annotators (Preston 2022; Muldoon et al. 2023, 2024; Perrigo 2023a) who, alongside the tech company programmers and campus telecommunications workers who build and maintain the digital infrastructure for faculty and other staff and students using AI, are interconnected along the same global supply chain.

A workers' inquiry connecting campuses to the global supply chain would map faculty and campus learning staff, instructional technology workers and the lower middle managers who manage and maintain university data, connectivity, learning management systems and AI tools and train faculty staff to use them. The Rutgers AAUP-AFT's 'wall to wall' organising model and 2023 strike offers an illustration of how to connect workers across campuses that can be replicated across systems and states (Pope 2024). This strategy allows cooperation among academic workers who have the skills and access to shut down campuses, thereby heightening the impact of collective action by faculty and other staff and students since, if faculty staff strike, the university could simply move classes online and run with AI generated lectures and grading.

Using a workers' inquiry with these aims in view would provide workers with the opportunity to identify and carry out disruptive forms of collective action to impede, undermine, slow and even block the use of AI. Workers up and down the global data supply chain have the power to engage in coordinated disruptive collective action across borders. For example, the objective of a 2019 strike threat by Sama data annotation workers in Kenya was to disrupt Facebook's flow upstream of usable data to apply leverage on the companies to meet their demands. They have since formed the African Content Moderators Union (Perrigo 2022, 2023a, 2023b). Academic unions can amplify their power by coordinating with the new Global Trade Union Alliance of

Content Moderators formed in Nairobi, Kenya, by unions from nine countries (UNI Global Union 2025).

Disruptive collective action is also possible on campuses where academic workers organise to gain a better chance of having their demands met. Academic workers operating at critical choke points have the leverage to refuse extractive AI (Alimahomed-Wilson and Ness 2018; Ovetz 2022). They can also act in solidarity with data workers elsewhere by demanding that university administrators terminate contracts with exploitative companies and apply pressure on AI vendors and training data companies in the Global North and South.

The organised collective refusal of extractive AI within the US can also be complemented by using the academic shared governance system to place roadblocks in the way of AI, including by exploiting faculties' primary responsibility for curricula, methods of instruction, academic standards and degree requirements, the making of campus policies and cooperation with accreditation agencies. The introduction of AI can be slowed, impeded or derailed by protecting academics' freedom to choose whether to use it in their classes and research. The shoring up of academic freedom in the US is urgently needed as staff and students face discriminatory censorship and, for non-citizens, Immigration and Customs Enforcement abductions and deportations (Thomas 2025). There have been significant attacks on academic freedom through crackdowns on anti-Zionist campus activism, including through the Department of State's use of AI to revoke student visas based on scans of news reports and social media activity (Caputo 2025). Campus workers, such as counsellors, disability service providers, diversity and other support staff, and lower middle managers who work closely with marginalised students, can protect these services by defining examples of automation that have proven ineffective, alienating and discriminatory (Weinberg 2024). Accreditation, state and campus policies can disqualify the use of AI 'teachers' as unable to meet the requirements of teaching a class. Students, faculty, and staff should, as acts of worker solidarity, have the power to assess and reject AI contracts that have a negative impact on working conditions, student learning settings and the environment, and that perpetuate labour abuses along the AI supply chain. Faculty serving on accreditation, curriculum and programme review bodies can develop campus policies allowing them to opt out of using learning management systems and to turn off plugins. Campus bodies can ban the use of AI in academic planning, hiring, promotion and tenure decisions.

Student-staff solidarity efforts, including open letters, have been successful in prohibiting the use of exam proctoring software at various universities in North America on the grounds of these tools being discriminatory, the fees being charged and the violation of students' privacy through data harvesting (Swauger 2020; Weinberg 2024). There are several recent examples of open letters being used to push back against AI, including for challenging the partnerships of AFT and the United Federation of Teachers with Microsoft and OpenAI; the open letter 'Stop the uncritical adoption of AI technologies in academia' addressed to universities of The Netherlands; and the 'Open letter from educators who refuse the call to adopt GenAI in education' from a global community of education professionals (Greene 2025). Faculty and student governance bodies can also obtain copies of contracts for AI, conferencing, learning management systems and plugin software to identify who owns student and faculty data. This information can be used to raise privacy and exploitation concerns with the companies that own and control the product of academic workers' labour.

A strategy to refuse extractive AI is needed to replace collaboration with the corporations and academic managers that want to impose it. Academic workers can use a workers' inquiry to broaden an understanding of how AI is being deployed as a neoliberal tactic to control and manage academic labour to produce more disciplined, productive and compliant students whose labour can be exploited on and off campus. Once we scratch below the surface myth of AI, we'll find management's newest labour control strategy. Then academic workers will be able to identify new tactics and strategies needed for an organised refusal of AI while expanding democratic control over academic labour.

Conclusion

As this chapter has demonstrated, AI is being used in higher education to undermine academic workers' power and cede core education infrastructure to for-profit AI vendors, with a self-defeating response from many large higher education and teaching unions in the US. Existing collective agreement language on AI in both the US and the EU largely prioritises strategies of collaboration rather than refusal. In contrast, this chapter has proposed learning from AI-related organising in other sectors and using a workers' inquiry to identify new tactics and strategies for coordinated worker collective action across the global AI supply chain.

Such efforts are beginning to take shape. At the University of Michigan the librarians and archivists bargaining unit (GLAM or Galleries, Libraries, Archives, and Museums, which includes Librarians, Archivists, and Curators) of the Lecturers' Employee Organization drew on SAG-AFTRA's strategies to refuse employer uses of AI to reproduce worker voices or likenesses without consent and to ensure appropriate use of AI (Michigan Daily News Staff 2025). After passing an assembly resolution calling for worker control of AI, the CFA established a contract article committee that developed new language for refusing AI in the California State University system (CFA 2024b). Similarly, UCU's report on AI concludes with recommendations for considering the impact of AI and was then followed up by a member survey on AI in the union's Loughborough branch in 2024. However, academic workers will need to ramp up disruptive tactics to counter the rapid proliferation of extractive AI in higher education.

The American Association of University Professors (AAUP) takes a bold step in calling for cross-sector organizing around AI, recognising:

> the importance of fostering solidaristic strategies across higher education, education more broadly, white-collar and industrial sectors, and civil society and grassroots organizations fighting on many fronts to establish bottom-up policy around generative AI. (Paris et al. 2025: 9)

Such a cross-sector vision provides a promising path forward and should be conducted in cooperation with unions across the global AI supply chain, including the Global Trade Union Alliance of Content Moderators, where worker organising is already underway.

Since AI is being used as a weapon in a strategy against workers and unions to erode contractual protections and rights, increase workload and diminish worker control over labour, it is crucial to exercise workers' power to refuse its use. A rejection of extractive AI speaks to a vision of economic democracy in which academic workers have autonomy and control over their work.

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Abbreviations

AAUP	American Association of University Professors
AFL-CIO	American Federation of Labor-Congress of Industrial Organizations
AFT	American Federation of Teachers
AI	Artificial intelligence
CFA	California Faculty Association
CLA	Collective agreement
EdTech	Educational technology (industry)
EU	European Union
GenAI	Generative AI
HER	Higher education and research
NEA	National Education Association
NVP	Notification, voice, participation (a collaborative strategy for dealing with AI in the workplace)
SAG-AFTRA	Screen Actors Guild-American Federation of Television and Radio Artists
UCU	University and College Union
US	United States
WGA	Writers Guild of America

Part 5
A way forward

Chapter 12
Afterword: Quo vadis, AI? Quo vadis, education?

Vassilis Galanos

Introduction

In March 2023, a cartoon design company called Marketoonist published a two-panel comic-strip titled 'AI written, AI read' in which a person, pointing towards a computer screen, says to another: 'A.I. turns this single bullet point into a long email I can pretend I wrote'; in the second panel, a person points at the screen, saying to another person: 'A.I. makes a single bullet point out of this long email I can pretend I read.'

Figure 13.1 **AI written, AI read, by Tom Fishburne** (Marketoonist, 26.03.2023)

Source: © marketoonist.com

The scenario will be all too familiar to most readers of this volume. Yet, the anecdote does not end here. In May 2025,[1] a Reddit user named Necessary-Drummer800 published a four-frame, manga-style comic strip featuring two colleagues, both dressed in smart casual attire. The first character, a conventionally male figure looking visibly fatigued in front of his laptop, thinks to himself, 'There's no way I can finish a 12-page report tonight.' In the following frame, he appeals for help: 'Hey, Co-pilot – I need you to generate a 12-page report from the 5 bullet points iarterly.doc.' Below, another colleague, conventionally female and evidently stressed upon receiving said report, reacts: 'Did Tim really just send me a 12-page report? I don't have time to read all that...'

1. 'AI will make Everyone more efficient!' by Reddit user r/singularity https://www.reddit.com/r/singularity/comments/1ko2wqu/ai_will_make_everyone_more_efficient

In the final frame, she too turns to technology: ‘Hey, Co-pilot: Summarize the report Tim just sent me into 5 bullet points.’ The post’s author notes: ‘Yes of course Chat GPT [sic] generated this.’ One commentator suggests: ‘You took this from someone else’ (Indol210beat, same post). Another replies: ‘This was AI generated’ (BadAdviceBot, same post). Indol210beat (same post) suggests: ‘No the joke/idea is original and they generated a new version with AI, still stealing.’ The same user directed this author to the original cartoon by Marketoonist.

Less than a month later, a variation appeared on a Facebook page[2] called Illogical Reasoning, this time styled as a vintage comic strip. In the first frame, a clearly drained colleague, conventionally female and clad in a casual blouse, is depicted in front of her laptop, thinking: ‘There’s no way I can finish this 20-page report tonight.’ In the second, she instructs: ‘ChatGPT, please generate a report from these 10 bullet points.’ The third frame features a conventionally male colleague in formal attire, who wonders: ‘Has Anna just sent me a 20-pager? I don’t have time to read that.’ And finally: ‘Copilot, summarise the report Anna just sent me into 10 bullet points.’

Humanity has reached a point in which it is hard to tell whether jokes about artificial intelligence (AI) are produced with or without AI, and where it is hard to identify the human-made jokes that gave the basis for the AI-made ones that are becoming more viral. In addition to this observation, this story is indicative of several persistent themes that are present in this volume. This Afterword offers reflections arising from the preceding chapters drawing, where relevant, upon the history of automated lecture halls to reassure readers that the current sense of AI-driven disruption is indeed embedded within a longstanding historical process – that society has the power to change. It concludes with proposals for future research and actionable steps for AI and higher education and research (HER), with particular attention to the trade union perspective. Before moving on, however, let the reader be reminded of the preceding chapters’ main takeaway messages.

In their context-setting chapter, Di Ridolfo and Ponce Del Castillo provide an overview of AI integration in education, highlighting the regulatory and governance challenges posed by the advent of recent AI systems that need addressing to preserve academic autonomy and safeguard working conditions. In Part 2, which focuses on sociotechnical considerations, Copeland discusses the impact of AI on intellectual property rights and professional needs from a trade union perspective, emphasising the need for policies that protect academic freedom and workers’ rights particularly in light of the academic environment’s commercialisation and privatisation. Reigeluth then critiques the automation of learning, examining the implications of AI for pedagogical practices and the need for a reevaluation of the goals of education as well as evaluation per se – all through a philosophical, sociological and media theoretical lens. Finally, Oliveira explores the digitalisation of general education, focusing on the existing privacy, data protection and unequal access to literacy issues exacerbated by AI, and calls for robust governance strategies to protect HER stakeholders in particular.

2. https://www.facebook.com/illogicalreasoning/photos/d41d8cd9/1118774366957237/?_rdr, posted by Facebook user Illogical Reasoning.

Part 3 zooms into the legal considerations. Fernandes presents and analyses the privacy and data protection threats posed by extended reality (XR) technologies in education, advocating comprehensive legal frameworks to address these challenges. Fernandes's findings on XR are lessons which are directly applicable within AI domains or immediately related. Ponce Del Castillo examines the implementation in higher education of the AI Act passed by the European Union (EU), offering a concise inventory of relevant terminologies, identifying gaps and suggesting ten actionable improvements to ensure compliance while protecting fundamental rights. Kivinen explores the intersection of copyright and generative AI (GenAI), highlighting the challenges educators face with AI-generated content and stressing the importance of responsible usage and legal compliance, as well as asking deeper questions about the contemporary appreciations of creativity. Mäntysaari examines GenAI's impact on intellectual property rights, particularly for academics, and argues that trade unions should be addressing these issues while reinstating the role of academics as guardians of scientific integrity.

Part 4 offers considerations on working conditions. Komljenovic analyses the workplace implications of post-AI EdTech and broader datafication for higher education, highlighting the challenges posed by platformisation, including surveillance, and advocating inclusive governance in EdTech operations. Hine discusses the cognitive, social and ethical implications of XR technologies in education, focusing on the challenges of integrating these with emphasis on the emotional and psychological challenges posed both by XR and associated technologies. Ultimately, Weinberg and Ovetz overview recent strategies on organising against AI in HER within the US trade union context, urging collective action and resistance to maintain control over academic labour and counter the exploitative aspects of AI technologies – lessons that can be useful for global contexts and also within the EU.

Taken together, the chapters contained in this volume demonstrate the immense complexity of the AI in HER landscape, where technical aspects such as data storage and algorithmic decision-making overlap with legal aspects such as intellectual property rights, social dimensions such as surveillance, personal aspects like emotion, and ethics in the case of recognising academic freedoms and scientific integrity. This proves the role of trade unions being as much polyvalent as crucial. With inspiration from the above, the following will offer an overview of the debate and some directions to move further.

1. Generative AI is the symptom, not the cause, of a degenerative HER sector

> 'One fails to see, although it could hardly be more obvious, that pessimism is not a problem but a symptom.' (Nietzsche 1968: 24)

Artificial intelligence is neither inevitable nor self-sustaining; it emerges from social interactions and decisions and relies fundamentally on user input. Much guided by Nietzsche's pedagogical lessons, aphoristically summarised in the above epigram, this Afterword suggests that AI's pessimistic or optimistic baggage are more outcomes than sources of the broader decadence in HER – a decadence that we are able to adjust creatively.

The challenges presently confronting HER are so immense that AI, the recent GenAI wave in particular, should be seen as a caricature of the persisting problems – a caricature similar to the cartoons described above. The advent of OpenAI's ChatGPT opens up possibilities for reflection about the status of HER: while AI tools represent one of the many challenges in the contemporary sector, they are ultimately a symptom rather than a cause of a deeper, ongoing decline in its values. The rise of GenAI is, in many respects, simply the latest confirmation of this trend – a confirmation made visible through increased automation, the proliferation of computerised instructions that are shaping the experiences of students, staff and administrators alike, and the unrelenting surplus production of texts in which predictable language is preferred: essays, applications, reports, articles and so on.

This is compounded by the entrenchment of metrics-driven systems: grades, excellence points, impact factors – all of which are grounded in a broader culture of status and ranking: 'likes', 'follows', 'subscribers', citizen scores, credit ratings: all militaristic in origin. To restate: *AI tools are outcomes, not origins, of our predicament*.

Franco de Benedetti, then Managing Director of Olivetti – a once-leading multinational office equipment manufacturer – noted this duality more than four decades ago:

> EDP (electronic data processing) seems to be one of the most important tools with which company management institutes policies directly concerning the work process conditioned by complex economic and social factors. In this sense EDP is in fact an organisational technology, and like the organisation of labour, has a dual function as a productive force and a control tool for capital. (Cited in Cane 1981)

Some further elaboration on this argument from the socioeconomic perspective is required prior to moving into the more technical aspects of the problem.

1.1 How the contemporary AI crisis in HER is the outcome of a declining education sector

Importantly, the idea of an 'automated classroom' is far from new and is developing hand-in-hand with the influence of Taylorist production on the HER sector. As Barbara Hof (2023) has demonstrated with historical precision, this idea emerged from early cybernetics and cognitivist visions, imagining the computer and technical teaching aids not simply as learning enhancers but as instruments of control, command and communication within the lecture hall itself. These ambitions have dovetailed with the increasing management of academics on short-term contracts, which saw a 25% increase over 22 years (Barnes and O'Hara 2002), the emergence of 'permanent temporariness' (Rasmussen and Tove 2012) and what has been called 'turbocapitalism' (Virilio 2012). Labels such as 'taxi professors' (Simbürger and Neary 2016), 'edu-factory speed' (Fleming 2021) and mechanisms like the Research Excellence Framework (see Readings 1996; Sørensen and Traweek 2022) have all contributed to a climate of escalating assessment and velocity. The result has been widespread alienation and estrangement among academic workers from their own intellectual products – which, in turn, is leading to a markedly diminished motivation to engage (Hui 2023). Under all these conditions – including minimal motivation for engagement, short-term contracts and students-as-numbers – can we (that is, staff, students and administrators) truly resist the temptation of ChatGPT?

This academic precariousness is deeply intertwined with broader social crises: gentrification, the housing crisis, platform and gig economy models (Baldwin 2021; Fleming 2021; Rabiei-Dastjerdi et al. 2022), and the 'TikTokisation' of everyday life (the news, war, global politics, social media; see Galanos 2023); an increasingly fragmented consumption of ideas and culture that is, at one and the same time, continuous yet lacking in cohesion and meaning. The history of the 'automated classroom', then, does not merely map to technological change; it is tightly correlated with the growing precariousness of HER workers and the emergence of human beings that Deleuze (1990) would call 'dividuals' within 'societies of control', whether in their cybernetic utopian or dystopian forms.

We must, therefore, turn to history as a rear-view mirror to discern what lies ahead. As Copeland (this volume) demonstrates from a trade union perspective, the recent historical decline of the HER sector has, in many ways, paved the way for AI tools, mirroring how earlier forms of automation accompanied periods of eroding labour rights during industrialisation. If anything, these AI tools – and the myriad challenges explored throughout this volume – present a critical opportunity for us to re-examine and reorient our demands and expectations regarding knowledge production and dissemination. As Reigeluth also shows (this volume), many of these theoretical tools about our evaluation of pedagogical goals are readily available – they might simply need some sharpening for purpose.

An immediate response to proclamations about the transformative power of AI can always be to invert the question. Rather than asking what AI will do to journalism, politics, human relations, management, business, psychology or education, one may reflexively remove AI from the equation and interrogate the purpose of the activity itself. In each case, one is compelled to ask: *what is this aspect of social endeavour truly for*? Most pressingly for us: *what is education for*?

Against the backdrop of the challenges faced by students, staff and administrators in HER – as well as the relentless hype generated by AI suppliers and vendors – it is clear that trade unions remain one of the key agents with the potential to influence how AI is adopted and implemented across the sector. Unions, along with the broader workers' movement, have a storied tradition of advocating the maintenance of skill levels amid the advent of new or reconfigured technologies; or indeed, of confronting technological shifts head-on. For this volume, my privileged position as reviewer of the submissions has afforded me insight into some of the latest developments in law, labour rights, critical theory, ethics and beyond, all of which shape this discussion.

Generative AI, for its part, offers the dubious promise – and, to a considerable extent, the reality – of efficiently producing the 'boring' sections of texts that are routinely sidestepped or disliked due to their routine predictability: the opening and concluding lines, proofreading, grammatical and syntactical tidying, idea generation, the concise summation of common-sense knowledge. In this way, it 'saves us time' – but to what end? Here, Marx's insights remain strikingly relevant:

> The shortening of the hours of labour creates, to begin with, the subjective conditions for the condensation of labour, by enabling the workman [workperson] to exert more strength in a given time. So soon as that shortening becomes compulsory, machinery becomes in the hands of capital the objective means, systematically employed for squeezing out more labour in a given time. [...] [Machinery] shortens the hours of labour, but, when in the service of capital, lengthens them; [...] it lightens labour, but when employed by capital, heightens the intensity of the labour. (Marx 2013: 285, 304)

This historical ambivalence, which has always attended technological change in the world of work – whether in the industrial sector or, as now, in the sphere of intellectual production – offers a salutary warning. Just as in the earlier anecdote, where automation enabled a cycle of endless production and summarisation, the drive for efficiency risks intensifying both the pace and the expectations of academic labour rather than emancipating us from its burdens; unless, that is, we invent systems of reward for the time gained using AI and adjacent automations.

2.2 How the contemporary crisis of AI in HER is the outcome of existing sociotechnical configurations in the academic world

To understand the nuances of generative AI's impact on HER, it is crucial, of course, to place it in the context of the broader trajectory of AI development as a technical project – a trajectory that, in retrospect, reveals how education itself has unwittingly contributed to the logic of automation. For a more detailed conceptualisation of the AI definitions above, see Galanos and Stewart (2024).

Symbolic AI, the earliest era, was predicated on the explicit coding of instructions – computers were given rules, formulae and procedures, much as educators provide 'instructions' for essay writing or problem-solving. What counted as 'intelligent' was simply the computer's capacity to follow instructions to a high degree of fidelity. This reflects the long tradition within academia of privileging those who could most faithfully reproduce established conventions – be they students or 'essay writing servitors' – whether through genuine engagement or rote replication.[3] The subsequent rise of connectionist AI, or machine learning, shifted the emphasis: now, computers were tasked with recognising patterns across large datasets, adapting models in accordance with previous inputs. Again, education had laid the groundwork for this, generating vast swathes of standardised essays, reports and exam scripts – a body that became, sometimes indirectly, the very fodder for AI systems as well as the essay mills and informal markets that have shadowed institutional learning.

Today's GenAI and adversarial neural networks, perhaps the synthesis of these tendencies, go a step further: they do not 'create' or 'generate' in any meaningful sense but rather rearrange existing data based on prompts, producing output that is statistically novel yet fundamentally derivative. This is the meaning of the word 'adversarial'. It is 'different' when set against the statistical backdrop of existing texts, but only so that

3. To quote James Joyce, punning on the ritualistic repetition of 'right' or 'correct' words found in predictable order: 'the rite words by the rote order' (Joyce 1939).

it is not detectable by plagiarism detectors looking for exact text matches. That such systems routinely pass plagiarism and originality tests is, ironically, a testament to the decades-long replication and normalisation of formulaic writing in our sector. In this light, we should not be surprised to discover that machines now excel at imitating the repetitive processes that have long been integral to academic production – almost as if we ourselves had been rehearsing for this moment of machinic mimicry.[4]

Institutional pressures are only reinforcing this cycle: large student cohorts, increasing demands for rapid assessment, the rise of learning analytics and pattern recognition, and the proliferation of student support mechanisms – all seemingly well-intentioned ('the road to hell is paved with good resolutions', as Rambach cautioned in 1811), yet all are accelerating the logic of automation. We thus vacillate between technophilic optimism and mounting unease. Remarkably, it has only been three years since the early rollout of GenAI technologies in the HER sector. And yet, industry advocates loudly proclaim high rates of adoption – claims that are difficult to substantiate over such a short period and which often function as self-fulfilling prophecies: AI is 'widely adopted', because the drumbeat of its adoption is relentless. Minimal stories of success construct grandiose hype statements followed by the mandate to adopt, adapt or lag behind and perish – if you don't use AI, others will.

As the preceding chapters of this volume make clear, we find ourselves at a crucial juncture. The decisions we make now – whether as educators, researchers, unionists, policymakers or indeed as students and workers – will determine the shape of our future. We must ask: *will we accept these technologies as they are, adopting them uncritically and accommodating their limitations*? *Or will we strive to shape AI, employing participatory and critical design to make it serve educational and social aims beyond the imperatives of speed and efficiency*? Perhaps, in the end, we will judge that the flaws run too deep and that resistance and structural change are the only meaningful options left to us. These are not easy paths to navigate, especially in an era of overwhelming AI hype and technological promise. But clarity on these options, and an awareness of our potential for 'otherwising' (to borrow a term from Azizov (2012)), remains essential if we are to reclaim agency from the ever-accelerating technological tide.

3. Future directions for research and trade union action in the AI-HER nexus: an actionable agenda

Reflecting on the preceding chapters, personal experiences and the wider context of technological transformation in higher education and research, the way forward emerges with increasing clarity: we must combine clear-sighted analysis with collective, organised action. This follows recent calls for 'collective discussions of how the educational AI community is co-engaged in political action that has varying impacts on different groups of people in various educational contexts' (Selwyn 2023). The spiral of

4. To quote German techno-pop band Kraftwerk (Schüte 2020): 'We are the robots' – not as in 'we are the robots who will take your jobs,' but as in 'we, the workers, are the actual robots, not the machines used in our organisation.'

automation, exemplified in both the opening anecdote and the history reviewed above, demands more than either anxiety or uncritical adoption. Instead, it calls for a research and action agenda that recognises both our situation and our capacities for change.

The following 12 proposals are themes in which, according to my judgement, further light needs to be shed, based on the chapters in this volume and a critical assessment of AI's history and the present status of HER.

– Defragmenting regulation

As Di Rodolfo and Ponce Del Castillo, as well as Ponce Del Castillo, have shown (both this volume), there is a pressing need to coordinate regulatory initiatives across the frameworks of AI in education at the level of the EU, Organisation for Economic Co-operation and Development (OECD) and United Nations Educational, Scientific and Cultural Organization (UNESCO) (horizontal alignment), alongside ensuring alignment with university-level policies (vertical alignment). Such harmonisation will prevent contradictory regulatory environments and encourage best practice to diffuse across borders and institutions.

– Intellectual property rights

Research must focus on safeguarding intellectual property for students, academics, administrators and other workers in the HER sector – whether teaching materials, articles or research data (see Copeland, Kivinen, Mäntysaari, all this volume). Transparency from publishers, and the introduction of robust opt-in or opt-out clauses for the academic material being used to train AI systems, are essential in an era where 'data' and 'content' can be so readily extracted by AI.[5]

– Evaluating AI plagiarism detection

We need a thorough understanding of so-called AI plagiarism detectors, many of which are based on adversarial network technologies that provide only probabilistic – rather than conclusive – results (see the technical justification above). The implications for fairness and due process in academic assessment are profound, while the accuracy and reliability of such systems demand urgent interrogation as there is a risk of false positives and false negatives in a manner similar to false positives and false negatives in AI-assisted healthcare diagnostic systems.

– Bias, discrimination and human judgement

Allied to the above, trade unions should be at the forefront of uniting those who are focused on combating discrimination (sex/gender, race/ethnicity, ability, age and so on) with the

5. Consider the growing controversy following Informa PLC (the business intelligence company that owns well-known academic publishers Taylor & Francis, Routledge, and CRC Press) agreement to collaborate with Microsoft to train AI models, using the aforementioned publishers' contents such as academic articles, reviews, book chapters, and more – without seeking any consent from the authors. https://www.informa.com/globalassets/documents/investor-relations/2024/informa-plc---market-update.pdf

trainers who are responsible for technological upskilling in AI literacy. The assumption that AI-generated writing can be detected is increasingly unreliable, especially when compounded by biases – whether algorithmic or human – as new cultural and medical associations shape perceptions and misperceptions about authorship[6] (*what are we willing to risk when stating 'this reads as if a robot has written it'?*).

– Quality of life and connection

Spaces that foster genuine, meaningful connection among the members of the HER community must be protected and cultivated. As the anecdote of the endless summarising and repackaging of text reminds us, the digital treadmill may save time but too often at the expense of authentic engagement. Putting Ponce Del Castillo and Hine's works (this volume) into the dialogue, the psychological stress raised in environments highly mediated by technologies that claim quantitative 'emotional recognition' is posing serious considerations about the wellbeing of people within the sector who feel permanently monitored; it effectively influences their understanding of self and the overall purpose of the workplace, including the role of academic freedom.

– AI literacy for all HER workers

Trade unions should take a lead in designing and delivering AI literacy programmes, tailored for HER workers at all levels, to ensure the power dynamics created by digital literacy gaps do not compound existing inequalities. In HER contexts, such programmes should not distinguish between ranks or status (students, staff or administrators) while, at the same time, due to AI's functions, they should be able to tailor such literacies for specific cases (see Oliveira and Ponce Del Castillo, both this volume). Special emphasis should be placed on, and trade unions are well-positioned to offer, critical AI literacy. This should go beyond mere upskilling, in terms of the competencies on the technical side of AI, to incorporate the skills required to recognise the challenges posed when AI is used in the HER workplace including, but not limited to, various undesired biases, exploitation processes (from time management to intellectual work), hidden labour, the environmental costs and more.[7]

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6. An exemplar case is the public attention received around a professor who identifies as autistic whose writing style was mistakenly criticised over email for being AI-written. Such assumptions are widely circulating especially in students' submission of coursework, with the power dynamics being much different there. https://www.thecollegefix.com/professor-with-autism-mistaken-for-ai-bot/

7. Critical AI literacy within the HER sector is, due to the rapidly changing environment of AI, a nascent field, with everal academics presently experimenting with methods, approaches, and production of relevant resources. For an overview of the debate, see Velander et al. (2024). A great starting guide can be found in the following open working document prepared by Lauren M. E. Goodlad and Sharon Stoerger in collaboration with the Rutgers AI Round Table Advisory Council and the Office of Teaching Evaluation and Assessment Research: https://docs.google.com/document/d/1TAXqYGid8sQz8v1ngTLD1qZBx2rNKHeKn9mcfWbFzRQ/edit?tab=t.0#heading=h.kgds7i8l6uca

– Addressing inequities of access

Consideration must be given to stratification within and between institutions and between students, who may not have equal access to advanced AI tools or the skills to use them well (see particularly Oliveira, this volume). This extends to different academic institutions' financial capacities to purchase AI licences or even develop their own and offer them to their communities, as well as individuals' affluency in the purchase of private AI tools. Lessons here can be drawn from the journalism sector – as Jones and Galanos (2025: 17) report, post-AI business models may 'exacerbate dependence on very few large platform companies for infrastructure, products, and services,' something that is aligned with the cautionary findings by Komljenovic (this volume). Critical engagement with the very value of such tools, of course, may set the entire notion of this competition into question.

– Investigating the reuse of education data beyond the intended functions and purposes

Research must scrutinise the usage, reusage and possible exploitation of education data when deployed in machine learning systems or elsewhere (see Komljenovic and Fernandes, both this volume), either directly, indirectly, in the short-term or longitudinally. The phenomenon broadly known as 'function creep', 'an imperceptibly transformative and therewith contestable change in a data-processing system's proper activity' (Koops 2021: 29), is very much applicable in the HER sector and further augmented through AI: academic output and administrative data (lectures, essays, articles, reports, student data, time scheduling data, and others) are subject to reuse for purposes and functions beyond the intended ones, with AI algorithms often lurking quietly in the background of managerial operations. Efforts towards protection via digital watermarking methods should be made and trade unions can call for ease of access for the protection of intellectual property and privacy under such techniques.

– Union traditions and tactics for organised engagement or refusal

Given the power trade unions can have within the workplace, comparative research is needed regarding how well-established, and how representative, union traditions are within university facilities and how their stance towards technology influences, or can influence, the adoption of AI in university settings. Union attitudes towards AI adoption or rejection reflect deeply embedded national, institutional and historical conditions – as explored in Weinberg and Ovetz (this volume) principally with reference to the United States. Europe's historical complexity invites further research in this area. As debates intensify between reform and abolition (borrowing from calls to 'seize the means of computation' (Doctorow 2023) versus recommendations for the radical 'abolition' of AI technologies (Benjamin 2019)), unions should be able to inform workers of their rights concerning the gradations between dissent from and positive engagement with AI technologies, navigating the complex dilemmas of digital resistance and digital access. Historical traditions of different factions between union confederations may reflect approaches to technology and this should be a factor taken into consideration (see, for example, Estanque et al. 2020; Soeiro et al. 2025; and the still relevant Hoffman and Waddington 2001[8]).

– The 'AI effect', interconnected technologies and policy adaptation

Trade unions and HER workers should remain alerted to the ways in which AI is becoming embedded within broader technological arrangements wherein the distinctiveness of 'AI' may become obscured over time. This is sometimes known as the 'AI effect': once AI achieves a state of banalisation, it is not considered to be AI anymore, in the same way that previous rounds of discourse about AI achievements under a broad 'AI' umbrella are now largely being replaced by GenAI parlance. Ongoing assessment is needed of how AI policy is evolving in response to this effect. In HER, language writing assistance tools (like Grammarly) offer good examples of policies at different levels facing challenges in terms of defining their 'AI-ness' and, for instance, being deeply subjected to learning outcomes and expectations and social conventions about their use.

Conclusion

In sum, the way forward is not purely defensive. Yes, HER workers and trade unions must guard against the most corrosive effects of obsolescence, cognitive offloading and disruption to skill ladders. But they must also move proactively so that the design of systems, software, policies and institutional practices – all the embedded social and algorithmic functions of HER – are subject to negotiation, redesign or even refusal.

At the core lies a political question: *are the values built into technological tools mutable, or are they intractably locked-in*? If the former, participatory design offers promise; if the latter, unions and communities of practice should not shy away from advocating wholesale rejection and, in any event, assisting in the construction of alternatives (Winner 1980; Catanzariti et al. 2026).

This understanding of AI's political place within education and research points to a vital role for trade unions, HER workers, governments and regulatory bodies. Motivated, well-supported action on the legal, employment, wellbeing, literacy and ethical challenges outlined above will better equip both leaders and communities for the struggles ahead. Europe's rich history of union organising among technicians, designers and educators is a crucial resource as we look to the future.

Returning to the scenario of this Afterword's opening anecdote: as long as we allow the cycle of automated production and rapid summarisation to dictate the tempo of academic life, we risk losing touch with the deeper purposes of our work – and of education itself. Yet, if we strategically harness collective agency, informed by both

8. An interesting phenomenon throughout the evolution of the relationship between digital technologies and trade unions is that trade unions themselves are exposed to the same risks and opportunities posed by computers, ICTs, social media, or AI, facing the same dilemmas such as the workforce they are called to represent: a mandate to 'catch-up' with the digital but also find out ways to resist. Literature is scarce, if not inexistent in this area, however, the aforementioned sources may offer a starting point.

research and solidarity, we might reclaim not just time but meaning. The question is not merely '*what will AI do to us*?' but – echoing earlier reflections – *what do we choose to do, together, with, without, and beyond* AI?[9]

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9. When, in the 1980s, information technologies were as much mythically hyped as AI is today, Langdon Winner closed his 1984 article playfully titled 'Mythinformation' with these words: 'Some observers forecast that the computer revolution will be guided by new wonders in artificial intelligence. Its present course is influenced by something much more familiar: the absent mind' (Winner 1984: 596).

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Abbreviations

AI	Artificial intelligence
EdTech	Educational technology (industry)
EU	European Union
GenAI	Generative AI
HER	Higher education and research
OECD	Organisation for Economic Co-operation and Development
UNESCO	United Nations Educational, Scientific and Cultural Organization
XR	Extended reality

Chapter 13
Conclusion and synthesis: AI governance in and for higher education and research

Aída Ponce Del Castillo

Introduction

This volume examines the integration of artificial intelligence (AI) in higher education and research (HER) from three main perspectives: sociotechnological; legal; and labour. Across these chapters a consistent pattern emerges: AI is presented as having the capacity to enhance education; however, its procurement and deployment rarely enhance worker agency or professional autonomy and often transfer control from public institutions to commercial actors, including the EdTech industry.

The twelve chapters demonstrate that these trends are neither inevitable nor accidental. They reflect choices about technological design, institutional procurement and regulatory frameworks. Chapter 1 set out by identifying three pivotal developments that are responsible for accelerating the adoption of AI: the Covid-19 pandemic and the acceleration of digitalisation; the emergence of accessible generative AI (GenAI) tools; and the proliferation of university-corporate partnerships. These developments are creating the conditions in which datafication intersects with human dignity, body and cognitive integrity, agency and pedagogical autonomy.

The volume also shows that alternatives exist. From Denmark's public AI infrastructure model to the organising strategies documented in different contexts, the chapters show that participation and collective action is a mechanism to reshape technological trajectories as well as forms of collective resistance in targeted use cases. A central question is whether institutions, policymakers, industry, start-ups, social partners, the HER community and other actors will act on these possibilities.

This concluding chapter synthesises the main findings, sets out three core arguments and formulates recommendations for HER institutions, trade unions and policymakers. It closes with a call to action for all stakeholders in higher education and research.

1. Synthesis of insights

1.1 The transformation is sociotechnical, not merely technological

The sociotechnological analysis in Part 2 takes as an entry point the rapid expansion of technological change, showing that AI integration is restructuring HER work and not just adding new tools. Rob Copeland (Chapter 2) shows how AI intersects with existing trends in the workforce such as precarious contracts, fragmented roles and work intensification. These dynamics are accelerating the commercialisation and privatisation of higher education. Trade union responses should address not only the AI tools themselves, but the political economy reshaping the sector's purposes and governance.

Tyler Reigeluth (Chapter 3) provides the philosophical grounding for understanding why teaching and learning resist algorithmic reduction. AI systems draw heavily on behaviourist models that emphasise training, reinforcement and optimisation – models which are flattening the plurality of ends and values in education. In contrast, teaching and learning involve complex assemblages of know-how and judgement across disciplines. They require debate, contestation and the collective articulation of different forms of knowledge. No single objective function can capture this complexity. The drive to automate evaluation thus exposes a reductionism that marginalises what cannot be quantified.

Pedro Oliveira (Chapter 4) examines digitalisation's impact on pedagogy and the teaching profession. He argues that technology adoption requires critical engagement rather than passive acceptance, and points out that educators must navigate these systems while fostering students' critical thinking. This navigation cannot be left to individual responsibility alone. It requires multi-stakeholder involvement, including HER workers, students, workers' representatives, vendors and the EdTech industry in what Oliveira terms 'societal technology assessments'. Technology integration must be guided by education's democratic purposes, not by efficiency alone.

These chapters show that AI is reshaping not only what HER workers do but also how their work is structured, evaluated and controlled. The redistribution of 'intelligence' and judgement between humans and machines mirrors earlier rounds of industrial automation in which control shifted from workers to systems designed according to commercial priorities.

1.2 Legal frameworks partially protect workers

Part 3 addresses the legal frameworks and reveals the presence of some systematic gaps in protection for HER workers. The chapters address issues of data protection, body and cognitive integrity, privacy, intellectual property and copyright, as well as regulatory inadequacy.

Elora Fernandes (Chapter 5) explains five specific privacy threats posed by extended reality (XR) technologies in education. Eye-tracking, emotion recognition and brain-computer interfaces enable the creation of what she calls biometric psychography profiles revealing individuals' interests, aversions and vulnerabilities, based often on their involuntary reactions. Data collection and processing happen in real time and at vast scale. Furthermore, there are risks associated with dual use where data collected for one purpose is allowed to serve another, while the bystander problem means even non-users' data is processed when others are using XR in shared spaces. These threats exemplify the invasiveness characterising contemporary educational technology.

Ponce Del Castillo (Chapter 6) examines the application in HER of the AI Act passed by the European Union (EU). The chapter translates the legal obligations into practical compliance tools, identifying the points of intervention relevant to collective bargaining. However, significant gaps emerge. Higher education faces six sector-specific challenges: transparency of procurement processes; allocation of responsibilities across value chains; safeguards for human oversight whilst preserving educator authority; ambiguity over prohibited uses like emotion recognition in lecture halls; unclear AI literacy requirements; and liability for harm. Where the obligations are unclear or weakly operationalised, the compliance risks become discretionary and undermine fundamental rights.

Kari Kivinen (Chapter 7) and Petri Mäntysaari (Chapter 8) address the intellectual property (IP) and copyright dimensions. Academic workers are facing legal uncertainties over the use of copyrighted digital content in teaching based not least on a lack of transparency about what training data is included and whether rightsholders' opt-outs have been respected. Key concerns span copyright compliance, confidentiality and data protection, while clarity is needed regarding training data provenance, text and data mining limits and the legal status of AI-generated outputs.

From a trade union perspective, Petri Mäntysaari emphasises that academics occupy diverse roles – creators, users, evaluators – each with distinct IP needs. Union policies should strive to achieve the best outcome for members in each role without prejudicing others, while recognising that academic freedom must be protected across all roles. Importantly, EU law protects research freedom, including when researchers use text and data mining and, in some contexts, GenAI tools, but IP and GenAI policies increasingly serve as tools for greater goals and thus require holistic perspectives.

Across these legal chapters, the underlying finding is not the absence of relevant principles but the difficulty of making them effective in practice in HER. Regulation is fragmented across levels, and it is product safety governance that is shaping AI regulation. If the European Commission's proposal on the Digital Omnibus is approved, legal certainty and enforceability in workplace practice could further deteriorate, depending on the final text. In parallel, voluntary guidelines lack enforcement and responsibility is often shifted to individuals. These factors may contribute to limited worker participation in technology governance.

Additionally, AI literacy needs to be treated as a core workplace right, not a peripheral activity. Even if future legislative revisions dilute the explicit obligations on particular actors, institutions and employers still need robust literacy frameworks to ensure lawful, rights-respecting deployment. AI literacy must extend beyond technical skills and include legal awareness (data protection, copyright, fundamental rights) and critical thinking, and must seek to enable workers to understand the oversight mechanisms. Collective bargaining remains the most immediate mechanism to translate into forms of worker protection key principles like academic freedom, professional autonomy, research integrity and AI literacy, while placing limits on datafication and monitoring by circumscribing them within defined, enforceable workplace rules.

1.3 Workers bear the impacts

Part 4 examines AI's direct impacts on HER workers and makes visible the often hidden effects on working conditions.

Janja Komljenovic (Chapter 9) argues that, despite the recent focus on GenAI, attention to platforms and datafication remains necessary because they are continuing to shape education processes and governance. EdTech companies routinely roll out new GenAI functions and present them as efficiency gains and time savers. At the same time, these platforms support surveillance and work analytics. Monitoring staff activities and calculating granular indicators of performance becomes technically simple. As Reigeluth's analysis also suggests, quantification pressures tend to marginalise those aspects of academic work that resist measurement.

Emmie Hine (Chapter 10) examines the cognitive and psychosocial impacts of extended reality on academic workers and shifts the focus beyond students. Design biases in XR hardware and software can exclude some groups of users. Prolonged use of virtual reality can be linked to dissociation, anxiety, increased perception of workload, reduced connection with colleagues and cybersickness, and with uneven effects across populations. Teaching with XR adds to the cognitive load, and educators themselves have to bear most of the work of integrating these systems. Existing research already links the integration of education technologies to higher levels of stress and anxiety among those standing at the front of the room.

Surveillance concerns are particularly salient in XR environments. Behavioural and emotion-related metrics derived from XR data remain of doubtful validity. Human interactions are complex and context dependent; reducing them to quantitative indicators, such as speaking time, gaze direction or frequency of contact, risks producing misleading analysis, conclusions and decisions. Meanwhile, continuous monitoring can have chilling effects on academic freedom and trust: if educators know that their movements and interactions in XR environments are being recorded and analysed, self-consciousness and hesitation are likely to be predominant. Surveillance anxiety encourages self-censorship, as documented in other online contexts.

Hine concludes with five recommendations for regulators: they should invest in training and support for faculty and other staff; prioritise inclusive design and access; set clear ethical guidelines for data and privacy; protect academic freedom through faculty representation in XR-related decisions; and encourage interdisciplinary research on the long-term impacts of XR.

Weinberg and Ovetz (Chapter 11) analyse organising strategies around AI in higher education. They draw mainly on US cases but point to lessons that can travel. They note that some large academic unions have so far focused on managing and negotiating AI adoption, while other unions and grassroot groups have taken a more confrontational stance towards extractive uses of AI. The authors set out a series of strategies, including the use of the concept of workers' inquiry to understand how AI is introduced, how it affects work and where the points of leverage lie. They argue that, in some cases, collective refusal of specific AI systems should remain an option when these systems undermine working conditions, academic freedom or student rights.

The chapter situates higher education within wider AI value chains, showing how academic workers are linked to data annotators in the Global South, to programmers and platform workers in technology firms, and to campus telecommunications workers building digital infrastructure. Workers' inquiry would be a way of mapping these connections and revealing how automation, control and the deskilling of academic labour are dependent on the large numbers of dispersed workers who are assembling, cleaning and annotating training data.

Across Part 4, the key point is that workers are experiencing AI's impacts directly through datafication, intensified surveillance, erosion of autonomy, increased cognitive demands and exclusion from governance. Value is being extracted from HER labour while working conditions remain unchanged at best or otherwise deteriorate.

2. Three interconnected arguments

This synthesis of all the chapters in this volume addresses three interconnected arguments about AI integration in HER.

2.1 Who benefits?

AI integration redistributes control and value towards the commercial technology providers.

Chapter 1 shows how university-corporate partnerships are creating vendor dependencies and lock-ins, shifting the control of education towards private entities. Chapter 6 argues that the AI Act does not directly address this dynamic, remaining primarily focused on market regulation, while Chapter 9 illustrates how datafication enables external actors to calculate, monitor and shape academic work. Chapter 11 documents worker resistance to these forms of control.

The thread of the analysis is clear. AI systems are not simply pedagogical tools that workers can deploy in line with their professional judgement; they are products designed with commercial imperatives, procured through opaque processes and integrated with limited worker participation. Often, control over curriculum design, assessment, student interaction and research processes is, in the process, being relocated to technology vendors.

This transfer of control has material consequences. Vendor lock-ins create dependency on proprietary systems while decision-making authority moves towards platform providers and public education missions fall into tension with the commercial priorities embedded in technological design. The automation of decision-making, evaluation and monitoring reflects particular values and interests rather than neutral efficiency. This transfer of control is not just managerial but a process in which data and pedagogical knowledge are converted into private and commercial value for some. This is why the Digital Markets Act (DMA) is relevant as a lever against gatekeeper-driven dependencies in the infrastructure layer on which EdTech ecosystems often rely, while the Digital Services Act (DSA) contributes a transparency and accountability lever where HER ecosystems are mediated by very large online platforms and search engines.

2.2 Who decides?

Current governance approaches do not ensure that meaningful worker participation frames the decisions about technological change.

The chapters that address governance show a pattern of worker exclusion. Chapter 1 describes decentralised institutional policies that individualise responsibility, while Chapter 2 emphasises that trade unions must gain seats at decision-making tables. Chapter 6 shows that the AI Act contains no meaningful requirements for worker participation, against which background Chapter 10 places HER workers at the centre of its recommendations on XR technologies. Meanwhile, Chapter 11 demonstrates that organising becomes necessary precisely because formal governance is sidelining workers.

This pattern functions at several levels. At European level, AI regulation operates with the limited direct involvement of trade unions. At national level, higher education policy often treats AI as technical innovation rather than workplace sociotechnical transformation. At institutional level, procurement and implementation decisions rarely involve academics, researchers or administrative staff. At individual level, workers are expected to adopt systems that often they did not choose and cannot easily contest.

The consequences go beyond procedural fairness. When those most affected by sociotechnological systems have limited voice in their design, procurement or implementation, those systems are unlikely to serve their needs or protect their rights. In contrast, collective bargaining provides a critical avenue to embed worker voice and democratise technology governance by formalising joint decision-making rights over procurement, deployment and impact assessments, among other rights.

2.3 What is being protected?

Existing legal frameworks provide limited counterweight in practice.

Chapter 5 reminds that purpose limitation, minimisation, security and protection by design are key data protection principles. This calls for a needs-based approach: tools should only be adopted if they are necessary to achieve a clearly defined, and proportionate, pedagogical goal. Chapter 6 analyses the AI Act's implementation in the context of higher education, in which there are no fewer than six sector-specific gaps that need to be addressed. Chapter 7 stresses the need for policy to strengthen the IP ecosystem in line with ongoing technological development, while Chapter 8 highlights that the limited transparency obligations on the providers of general-purpose AI models make it harder for copyright holders to understand whether their works have been used and thereafter to enforce their rights. The training of GenAI models may still infringe copyright, but the most fundamental problems relating to the deployment of GenAI in higher education and research are not limited to intellectual property but relate to integrity and scientific knowledge.

The consequence is a tendency to individualise risk and liability, with HER workers becoming the last line of defence against privacy harms, IP infringements, and bias and discrimination. These chapters also establish a consistent logic: the legal frameworks contain relevant principles and protections, but their application to AI in higher education contexts remains unclear, incomplete or unenforced. HER workers facing AI integration thus enjoy only partial and uneven protection.

3. Recommendations

AI adoption and deployment are a question of political economy and governance, not of technological inevitability. The recommendations below are guided by the principle of the subordination of technology to the education mission and the preservation of other fundamental tenets, and are directed to three primary audiences: HER institutions; trade unions; and policymakers.

3.1 For HER institutions

Higher education institutions bear direct responsibility for how AI integration and deployment affects their workers and communities. The following actions address the governance questions identified across the chapters:

1. Ensure transparent procurement processes

All AI procurement decisions should follow open procedures with published criteria. Workers and their representatives should have access to information on which systems are being considered, their capabilities, data requirements and likely impacts on working conditions.

2. Adopt a needs-based approach to AI procurement and deployment

The principles of data protection– such as purpose limitation, data minimisation and proportionality – should be applied to institutional decision-making. AI systems should only be introduced where they are necessary to achieve clearly articulated education objectives, where they are compatible with professional autonomy and academic freedom and where clear limits on monitoring and evaluation are defined.

3. Create meaningful spaces for worker participation in technology governance

Bodies should be established with decision-making powers, not only consultative roles, that encompass the elected representatives of faculty staff and other academic workers. These bodies should shape AI procurement, implementation strategies and ongoing evaluation. Participation must be resourced and recognised as part of working time.

4. Invest in genuine AI literacy for staff

Training should be provided that covers technical aspects, legal obligations and rights including GDPR and AI Act requirements, ethical issues and implications for workload and evaluation. These programmes should be designed in conjunction with worker representatives with a view to integrating them into professional development rather than treating them as optional extras.

3.2 For trade unions

Trade unions emerge throughout this volume as crucial actors capable of shaping AI integration. The following actions would enhance their capacity:

1. Integrate AI systematically into collective bargaining

Collective agreements should address the range of risks documented in this volume: datafication and surveillance; privacy intrusions that undermine dignity; intellectual property appropriation; work intensification and cognitive overload; erosion of professional autonomy; the psychological and cognitive impacts of XR; algorithmic management; and health and wellbeing. Bargaining needs to be specific and comprehensive, not limited to general principles.

2. Develop and deliver critical AI literacy programmes

As Chapter 6 argues, AI literacy is a core workplace right. Unions are well placed to provide training that goes beyond technical skills to include legal awareness (GDPR, copyright, fundamental rights), critical understanding of AI systems' limitations and biases, knowledge of the oversight mechanisms and the ability to recognise and contest harmful uses.

3. Demand transparency on data, algorithms and surveillance

Negotiated agreements should specify what data institutions collect, who accesses them, how they are used and under what circumstances they are shared. Clear limits should be established on monitoring, while institutions should be required to provide workers with access to the data held about them alongside mechanisms to correct inaccurate or unfair processing. The expansion of surveillance, and its chilling effects on academic freedom, needs to be documented and this evidence used in bargaining and, where appropriate, litigation.

4. Build cross-border networks and negotiate IP protections

European and international trade union structures should be used to share strategies, bargaining outcomes and legal precedents on AI at work. At the same time, intellectual property clauses need to be negotiated that address the questions of the ownership of AI-assisted work, the use of academic outputs for model training and the appropriate attribution of AI-generated content, while ensuring that these arrangements respect academic freedom in all roles.

3.3 For policymakers and regulators

Regulatory frameworks shape the context within which institutions and workers operate. The following policy options address the gaps which this study has identified:

1. Ensure robust enforcement of the DSA and the DMA in ways that support institutional autonomy and accountability in AI-enabled EdTech ecosystems.

Under the DMA, enforcement should be prioritised as a means of reducing the gatekeeper-driven dependencies on the core platform services used as the infrastructure layer for EdTech and AI deployment; this should help limit lock-ins and widen real procurement choices. The DSA should be cited where higher-level HER ecosystems are mediated by online platforms through the transparency and systemic risk governance obligations which apply to very large online platforms and very large online search engines, including requirements to assess and mitigate the systemic risks linked to their services. This can reduce structural dependence.

2. Mandate meaningful worker consultation in AI deployment

Regulation should require institutions to establish procedures that ensure workers and their representatives participate substantively in decisions about AI adoption. Information provision alone is insufficient. Workers should have a voice in procurement decisions, implementation strategies and ongoing evaluation.

3. Strengthen intellectual property protections for academics

The use of scholarly labour in commercial AI development must be addressed, while transparency should be required about training data sources. The legal status of AI generated outputs needs to be clarified, and attribution and control protections for human creators assured, in line with the concerns raised in chapters 7 and 8.

4. Limit intrusive surveillance and function creep in HER workplaces

The prohibitions on emotion recognition and related practices should be clarified and extended so that they cover biometric surveillance in higher education contexts including gaze tracking, movement tracking, brain data and physiological monitoring. Safeguards must be strengthened against data collected for one purpose being reused for another, particularly where education data such as lectures, essays and interactions are repurposed.

5. Require algorithmic transparency and ex ante impact assessments

Institutions and technology providers should be mandated to disclose how AI systems function, what data they are using and what documented effects there are on working conditions including workload, evaluation and surveillance. Comprehensive impact assessments on working conditions, professional autonomy, privacy, intellectual property and academic freedom should be drawn up before AI systems are deployed. These assessments should be public, they should incorporate worker input and they should have real consequences for deployment decisions.

These recommendations recognise that regulation alone cannot solve the problems identified in this volume. However, regulatory frameworks, institutional rules and collective agreements may either enable or constrain institutional and corporate behaviour. Closing the current gaps and centring worker protection would materially shift the terrain on which other actors operate.

Conclusion

This volume documents that AI integration in HER is proceeding with minimal input from those whose working lives are most directly affected. Datafication is invasive and can threaten human dignity, integrity, autonomy and academic freedom. Meanwhile, corporate dominance is accelerating and regulatory frameworks are struggling to accommodate the complexity of the sector. Worker exclusion from governance is frequently systematic rather than incidental.

Addressing AI requires confronting broader questions about education's purpose, governance and political economy. The commercialisation and privatisation of the sector, the proliferation of precarious contracts, the intensification of work and the subordination of education missions to market imperatives all preceded AI and are creating the conditions which facilitate its problematic integration.

This diagnosis implies that responses which are limited to AI alone will prove insufficient. The challenges facing HER workers require structural change, not merely better AI systems. However, AI's deployment provides a crucial opportunity: the visibility of surveillance practices, the obviousness of the transfer of control and the tangibility of professional autonomy each provide clear impetus for action.

Readers of this volume – academics, trade union representatives, policymakers, students – face a choice. One path accepts AI integration as presented: adopt the systems designed by corporations, accommodate their limitations and individualise the responsibility for navigating their harms. This path leads to deepened corporate capture, intensified surveillance, eroded autonomy and dignity, and degraded working conditions. The other path is based on organising to reshape AI integration according to anticipatory governance, democratic principles and workers' rights. This path centres professional judgement, protects fundamental rights like privacy and dignity, ensures transparency and accountability, and subordinates technological systems to the education mission rather than the reverse. This path requires coordination across actors, borders and sectors, and, above all, it demands that the collective response be sustained.

The insights in this volume demonstrate that this second path is feasible. Collective bargaining can realise actual protections. Institutions can make different choices. Regulation can be re-focused to protect workers' rights. The question is no longer what should be done; the chapters have addressed that. The question is, rather, how readers will act on the answers that these chapters have set out.

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Abbreviations

AI	Artificial intelligence
DMA	Digital Markets Act
DSA	Digital Services Act
EdTech	Educational technology (industry)
EU	European Union
GenAI	Generative AI
HER	Higher education and research
IP	Intellectual property
XR	Extended reality

Annex
AI systems used in education

This Annex provides a non-exhaustive overview of AI-enabled systems currently marketed for use across different levels of the education system, with a particular focus on higher education and research. It is not a comprehensive inventory, nor does it aim to measure prevalence or actual uptake. Rather, it offers some illustrative examples intended to give readers a structured snapshot of the types of applications available on the market at the time of compilation. For this purpose, the following criteria guided the selection: (1) a specific claim of the use of AI by the provider; and (2) a focus on tools designed for education, whether for students or educators. By mapping real-world AI applications, the Annex contributes to understanding the opportunities and risks of AI in higher education and research.

The examples were compiled from contributions by education trade union representatives and researchers during the European Trade Union Committee for Education (ETUCE) meeting on 30 June 2025, complemented by publicly available vendor documentation and product information available online as of September 2025. The URLs were accessed in May 2025. This Annex also informed the ETUCE's contribution to the European Commission's targeted stakeholder consultation on the classification of AI systems as high-risk, open from 6 June to 18 July 2025.

Inclusion of an application does not imply endorsement and does not constitute an assessment of legal compliance, effectiveness, accuracy or appropriateness for educational use. Descriptions may reflect provider claims and should be independently verified where used for governance, procurement or research purposes. The list reflects tools marketed but not necessarily deployed in EU education institutions.

The features and functionalities of these systems may evolve rapidly and are subject to frequent updates or modifications. The information reflects the situation as of September 2025 and should be understood as indicative snapshots of current use cases.

Table A1 **AI systems used in education**

Name	Main functions	Description	Education levels of use
Compilatio Magister https://www.compilatio.net/en/magister	Anti-plagiarism AI detector Grading Learning management	Compilatio Magister is a tool used in academia as a plagiarism checker for mono and multilingual plagiarism. In addition, it can be used to identify content written with generative AI as it recognises writing patterns specific to AI-generated text	Higher education and research
Copilot for schools	General tool. It can be used as: Teacher assistant Grading Learning management	Generative AI tool used for a variety of tasks such as creating lesson plans, generating quizzes and presentations, personalising learning materials and providing instant feedback	All levels of education
EduFace https://www.eduface.me/	Grading AI detector	AI base, trained on education data and specialised in six areas: law, economics, social sciences, STEM, humanities and health sciences. It is used for formative feedback on student writing assignments and checks text authenticity (has it been written with AI or not?)	Secondary education Higher education
Feedbackfruits https://feedbackfruits.com/	Teaching assistant Grading	Teaching assistant incorporating course/activity/programme design. Provides real-time feedback, data on students' performance and standardises assessments	Higher education
Gradescope (by Turnitin) https://www.gradescope.com/	Assessment creation Grading	Platform used to create and grade assignments; includes functions for grading paper-based, digital and code assignments	Secondary education Higher education
Graide https://www.graide.co.uk/	Grading	End-to-end assessment and feedback platform, used for both formative and summative assessment. The platform provides an automatic grading process and generates personalised feedback to students. It promises to reduce grading workload by up to 90%. 'When a student submits their response, an AI model evaluates it, predicting a grade and providing feedback with a confidence score. If the AI's confidence is high, the response gets a quick review. If not, it goes through a detailed check. Once reviewed and approved, the feedback is sent to the student. The process ends with the AI model being updated to improve future predictions.'	Vocational and professional development Further and higher education

Name	Main functions	Description	Education levels of use
Keath.AI https://keath.ai/	Grading	Keath.AI uses a specialised small language model architecture used for student assessment. It is used for both summative and formative assessment. It promises to save educators 480 hours per semester in grading	Secondary education Higher education Exam boards
Kira https://www.kira-learning.com	Grading Anti-plagiarism Learning management	Kira is an AI platform based on machine learning technology used for personalised education at scale. It includes different functions: **Kira grading**: automatically assesses all assignments and provides detailed feedback, highlighting areas for improvement. Educators can review the grading. **AI teaching assistant**: receive personalised recommendations for reteaching, scaffolding or enrichment **Context-aware feedback and scoring**: AI analyses student responses to provide detailed, constructive feedback, highlighting areas for improvement and reinforcing key concepts before grades are released	Primary and secondary education Vocational education and training Higher education
Parcoursup https://www.parcoursup.gouv.fr/decouvrir-parcoursup/parcoursup-c-est-quoi-1061	Student admission	Parcoursup is a national platform used in France for pre-registration in the first year of higher education. Whereas the system does not examine or rank applications – as this is performed by university academics – the system has an algorithm that manages the distribution of offers. 'The algorithm calculates, for each programme, the order in which admission offers are sent to candidates.'	Higher education
TeacherMatic https://teachermatic.com/	Teaching assistant Grading	AI-based platform used to create education resources (e.g. lesson plans, rubrics, reading lists and quizzes). AI generators act like personal assistants for educators and education teams. 'Lesson observation prompts' provide key areas to observe in a session within a named specialist area on a given session topic. It includes grading/feedback features	Primary and secondary education Vocational education and training Higher education

Name	Main functions	Description	Education levels of use
Turnitin https://www.turnitin.com/gateway/index.html	Anti-plagiarism Grading	It is used with a double function: 1. preventing plagiarism in student work by highlighting similarities to the collection of internet, academic and student paper content 2. provides feedback and grading features. 'AI-powered workflows increase feedback quality, consistency, and cut grading time in half.'	Secondary education Higher education
Khanmigo https://www.khanmigo.ai/	Teacher assistant Grading	The systems works as an AI-based personal tutor and teaching assistant. It has different functions and a tailor-made dashboard for teachers, students and parents. The functions for teachers include creating learning objectives, refreshing content knowledge in various subjects, planning and preparing classes, and summarising student work to assess progress	Primary and secondary education
Smart School https://www.smartschool.be/	Teacher assistant Learning management	Digital school platform that integrates communication, administration, e-learning, assessment process, data analysis and student monitoring. It is mainly made for the Belgian education system. Not all the functions of the platform use AI-based features. However, some of them include learning analytics, such as: 1. comparing the results of two school years of a group of students 2. comparing the results of one course to the results of all courses 3. tracking the evolution of the number of students in detail 4. following the certificates obtained and analysing the report of the class council's opinions and the results obtained 5. obtaining an overview of the evolution of absences	Primary and secondary education

Name	Main functions	Description	Education levels of use
Fobizz https://fobizz.com/de/	Tool for teachers	**Chat with AI**: AI chat features gives instant support for teaching strategies, lesson planning, etc. **AI character chat**: have the AI simulate different characters and engage in conversations **AI .pdf chat**: ask questions and generate different text types and assignments based on .pdf files **AI assistants catalogue**: discover AI chatbots for everyday school life **Customised AI assistants**: create and share chatbots with specific background knowledge and precise instructions **AI prompt lab**: find pre-written prompts and inspirations for a variety of use cases	Primary and secondary education
Snappet https://snappet.org/	Digital learning assistant	Adaptive learning platform for primary school. Extra adaptive practice for each student at his or her own level – with immediate feedback. Customises learning paths for students with specific needs. Provides challenging assignments designed to enrich students. Strengthens fluency with adaptive, timed exercises	Primary education
Gynzy https://www.gynzy.com/nl-nl	Complete digital teaching platform for primary schools	Digital learning tools for primary education in The Netherlands. Tailor-made training. Learning objectives are automatically available for each student. Evaluates learning outcomes. 'Much of what you'll find in Gynzy is designed to help you save time. In Gynzy, for example, you never have to check the assignments your students make.' https://www.gynzy.com/nl-nl/waarom/perfecte-aanvulling-in-jouw-klas https://www.gynzy.com/nl-nl/pakketten#pakketten	Primary education

Name	Main functions	Description	Education levels of use
FelloFish https://www.fellofish.com/#teachers	AI-powered feedback platform for teachers and students	Various uses: 1. AI assistant for corrections, giving students individual feedback on their texts and tasks. 2. Dashboard for teachers on individual students' progress. Dashboard on the student side as well. 3. Helps 'better allocate your resources and supports you in everyday teaching' (note: insufficient further information about this on the website.)	Primary and secondary education
Century Tech AI https://www.century.tech/artificial-intelligence/		'AI is being used in schools across the world to empower teachers, providing them with the data they need to provide students with a personalised education. But how does it work, and how can you tell whether a product that claims to use AI actually does use AI?'	Primary and secondary education Adult learning
MagicSchoolAI https://www.magicschool.ai/	AI platform and assistant for educators and students	'Award-winning AI for educators that saves time, prevents teacher burnout, and creates immersive learning experiences for students. The leading AI for schools that can be customized for your district's goals and needs to drive student outcomes.'	Primary and secondary education
Rockett AI https://rockettai.com/	AI-powered teaching assistant for schoolteachers	The platform offers a curated suite of AI tools built to support lesson planning, teaching and administrative tasks. 'By saving you time and simplifying your workload, we help you focus on what matters most – inspiring and educating your students.'	Primary and secondary education
Squirrel AI https://squirrelai.com/	Adaptive learning	Squirrel AI has an algorithm that adapts to individual students to help keep them more engaged. It includes a profiling feature	Primary and secondary education
Acuity https://acuity-app.com/	Learning companion	AI homework helper for smarter studying. 'The most powerful AI assistant with clear, detailed and educational explanations.'	Primary and secondary education
Writable https://www.writable.com/		For teachers: AI-generated feedback, comments and scoring. Antiplagiarism features. For students: originality check, antiplagiarism, grammar aid/suggestions	Upper primary and secondary education

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Governing Artificial intelligence in the Higher Education Sector

Sociotechnical perspectives, regulatory challenges and working conditions

Edited by Aída Ponce Del Castillo

Artificial intelligence has become a prominent feature of higher education across Europe. Universities are deploying AI systems in teaching, assessment, student services, research and decision-making. More than technical upgrades, these are institutional decisions about authority, responsibility and professional and pedagogical autonomy.

This volume offers a systematic interdisciplinary analysis of AI governance in higher education. Thirteen contributors from legal, sociotechnical, labour, intellectual property and critical theory fields analyse how decisions on control, accountability, ownership and evaluation shape AI use.

The volume identifies three structural dynamics with significance beyond the sector.

The first concerns how universities organise governance architecture. Procurement commitments increase universities' dependence on commercial vendors, whose AI models are trained on datasets that may incorporate institutional and academic materials, requiring careful attention to intellectual property and copyright obligations. Existing regulation, including the EU AI Act, approaches AI through a product safety model centred on risk classification, with limited scope for worker participation. In parallel, institutional policies often fragment accountability and expand surveillance capacities, reinforcing power asymmetries.

The second addresses the transformation of academic work. AI is introduced with the promise of efficiency, yet can lead to work intensification and performance tracking. Behavioural and biometric data about staff may be collected through systems with limited collective oversight.

The third concerns how learning and teaching are conceived. Many AI systems translate complex educational processes into quantifiable outcomes, narrowing definitions of intelligence and privileging evaluation that technology can measure and optimise, sometimes at the expense of professional autonomy and academic freedom.

By treating AI adoption as a governance issue rather than a technical one, the book connects higher education to broader debates about institutional autonomy, public sector digitalisation, professional independence and reliance on technology providers. It shows how procurement, regulation and governance choices shape universities and the knowledge they produce.

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