

# Implications of artificial intelligence for academics' work: a sociotechnical perspective based on podcast episodes

Maarten Renkema

*Faculty of Behavioural, Management, and Social Sciences, Universiteit Twente, Enschede, The Netherlands, and*

Aizhan Tursunbayeva

*Department of Business and Economics, University of Naples Parthenope, Naples, Italy*

## Abstract

**Purpose** – The increasing adoption and use of artificial intelligence (AI) is transforming how academics perform core activities, ranging from research to teaching and academic services. This paper empirically examines this phenomenon and its implications through a sociotechnical systems lens, analyzing changes in core activities and the multilevel factors that shape them.

**Design/methodology/approach** – This study adopts a qualitative design, employing a Podcast analysis. Based on 66 publicly available podcast episodes, we explore changes in academic knowledge work and examine the factors shaping them.

**Findings** – The findings show that the use of AI is changing academic work in ways that go beyond altering day-to-day activities. By interpreting the results with sociotechnical systems theory, this research identifies factors and emerging tensions at the individual, technology, organization and societal levels that together shape how AI changes academia.

**Originality/value** – Analyzing these sociotechnical factors, we introduce the academic AI-transformation framework (AAITF), offering a novel lens for understanding the consequences of AI for academics. Building on existing research, this study goes beyond the focus on single activities or levels of analysis, offering a more holistic understanding of how academic work is changing with AI.

**Keywords** Artificial intelligence, AI, Academia, Sociotechnical systems, Podcast

**Paper type** Research article

## 1. Introduction

Artificial intelligence (AI), such as both machine learning and large language models (LLMs) like GPT, is reshaping how work is conducted in higher education (HE) (Huang *et al.*, 2025; OECD, 2026). Academics, universities and research institutions are increasingly integrating AI tools into scholarly workflows. Early studies indicate a rising adoption rate: one survey found that 22% of researchers were using AI tools like ChatGPT (Owens, 2023), while another global study reported a 44% adoption rate among 5,000 researchers (Hrycyszyn and Eassom, 2025).

The rapid development of AI and its growing adoption in HE have profound implications for the future of academic work. Indeed, AI systems are already reported to assist in various aspects of scientific writing and manuscript preparation (Kwon, 2025), including editing and proofreading, drafting abstracts (Gao *et al.*, 2023), compiling literature reviews (Kacena *et al.*, 2024), supporting coding tasks (Bucaioni *et al.*, 2024), conducting statistical analyses (Huang *et al.*, 2025), generating research ideas, formulating hypotheses (Winn, 2024) or identifying research topics (Rashidov, 2024). In teaching, AI is used for content generation, providing



© Maarten Renkema and Aizhan Tursunbayeva. Published by Emerald Publishing Limited. This article is published under the Creative Commons Attribution (CC BY 4.0) licence. Anyone may reproduce, distribute, translate and create derivative works of this article (for both commercial and non-commercial purposes), subject to full attribution to the original publication and authors. The full terms of this licence may be seen at <http://creativecommons.org/licenses/by/4.0/>

Information Technology & People  
Vol. 39 No. 8, 2026  
pp. 129-149  
Emerald Publishing Limited  
e-ISSN: 1758-5813  
p-ISSN: 0959-3845  
DOI 10.1108/ITP-11-2025-1654

feedback, instructional design (Tan *et al.*, 2025) and to support student learning (Chang *et al.*, 2022; Pillai *et al.*, 2024). Meanwhile, its adoption simultaneously raises critical concerns about ethics, academic integrity and knowledge acquisition, critical thinking and learning (Izak *et al.*, 2025; Kwon, 2025), and about increasing digital divides and unequal access to technology (Dwivedi *et al.*, 2023; Miao and Holmes, 2023). In response, supranational institutions such as UNESCO and OECD have recently developed practical guidance on the ethical adoption of AI in educational contexts (Miao and Cukurova, 2024; Miao and Holmes, 2023; OECD, 2026).

Although research on AI's consequences for education has swiftly developed (e.g. Miao and Holmes, 2023; Strzelecki *et al.*, 2024; Wang *et al.*, 2024; Zawacki-Richter *et al.*, 2019), current knowledge is mostly available on the adoption of AI, its use cases, technical AI systems or direct human–AI interactions. Thus, the broader impact of these technologies on the work and tasks of academics remains largely unexplored, which is an important omission as academics are key actors for accessing, creating, disseminating and deploying knowledge and therefore central to understanding how AI shapes knowledge work.

A few exceptions exist, such as the recently published framework on changes in academic knowledge work (Renkema and Tursunbayeva, 2024), or studies from a special issue on generative AI (GenAI) in HE (O'Dea, 2024). However, the questions of how AI use will change academic work and what shapes these (potential) changes remain unanswered. Moreover, existing studies have explored the impact on specific academic activities (such as research or teaching) or the barriers to such activities in isolation (Al-Bukhrani *et al.*, 2025), leaving the interplay between individual work (design), organizational complexities and societal developments unexplored and undertheorized. As a result, existing accounts struggle to explain how and why AI-transformation take place in academia.

This paper addresses these gaps by examining how AI shapes academics' work, exploring the key drivers and barriers and introducing the academic AI-transformation framework (AAITF) – a conceptual framework drawing on systems thinking and socio-technical systems theory (STS). First, systems thinking informs our multilevel approach (Klein and Kozlowski, 2000), enabling us to explore how factors at different levels influence one another through feedback loops and dynamic interactions. Then, STS theory informs our framework by emphasizing the interdependent relationship between social and technical components (Pasmore *et al.*, 2019; Trist and Bamforth, 1951), shaping the use and consequences of AI within HE institutions' environments. Together, these theories capture the complex interplay among organizational design (social), emerging technologies (technical) and evolving academic work, offering a comprehensive understanding of how and why AI transforms teaching, research and academic services and informing strategies for effective integration of AI in academia. Through the development of the AAITF framework, this study contributes to the HE, knowledge work and AI-transformation literature by integrating STS theory with work design principles, and offering novel empirical insights into how a combination of top-down and bottom-up processes shapes AI-driven transformation of academic work. In doing so, we respond to calls for attention to multilevel sociotechnical factors that can jointly shape its use in HE (Renkema and Tursunbayeva, 2024), while also offering actionable guidance for practitioners. These insights can help academic institutions design STS and organizational change initiatives to respond to rapid advances in AI.

To uncover AI's implications for academics and align with recent calls for the use of novel data sources and digital methods in AI research (Orlikowski and Scott, 2023), we adopt an innovative research approach. Specifically, we employ a qualitative research design centered on podcast analysis (Kulkov *et al.*, 2024), systematically examining 66 episodes about AI in HE. This approach enables us to examine potential trajectories and factors of influence, as currently discussed by leading experts in the field.

## 2. Theoretical background

### 2.1 AI and work design in academia

AI is often defined as “the frontier of computational advancements that references human intelligence in addressing ever more complex decision-making problems” (Berente *et al.*, 2021, p. 1435). With the increasing integration of AI, human work in HE remains indispensable. Because it is not entire jobs but rather discrete tasks that are most susceptible to automation, academic work will likely involve intense interaction between humans and AI (Bechky and Davis, 2025; Parker and Grote, 2022a). In this evolving landscape, it becomes essential to incorporate work design considerations when assessing the potential effects and outcomes of AI in HE, for example, in terms of the quality of academic work, the level of autonomy, social relations, but also its implications on knowledge, feedback and learning (Parker and Grote, 2022a). Work design is related to the content of a job, in terms of work tasks, activities, relationships and responsibilities (Parker, 2014). While existing studies have helped to better understand current changes in academic work design (Barros *et al.*, 2023; Renkema and Tursunbayeva, 2024), they are less suitable for understanding how and why academic work is changing. Proactive design approaches are needed not only to navigate these shifts but also to intentionally shape the future of academic work. This requires a deep contextual understanding to ensure that technology is appropriately integrated within existing workflows and academic environments (Parker and Grote, 2022a). A focus on the individual-level changes is useful to study the implications of AI, but misses the fact that AI technologies shape and are shaped by the social context in which they are used. Moreover, this social context is important because academic work is deeply embedded in institutional settings that configure what AI tools get adopted and used.

This perspective aligns with STS principles, which provide a compelling lens for analyzing the interplay of social and technical elements in HE (Appelbaum, 1997). For instance, technological factors (e.g. system transparency) and societal dynamics (e.g. regulation, cultural readiness) have already been noted to jointly produce different scenarios for AI’s impact on academic professions (Grimes *et al.*, 2023).

### 2.2 Sociotechnical systems theory (STS)

STS theory was developed within the 1950s British coal mining industrial context (Trist and Bamforth, 1951). It was intended to recognize the “ways in which the behaviours of human actors affect the operation of technology” (Pasmore *et al.*, 2019, p. 67). STS emphasizes that technological success depends on its integration with the social system, including the knowledge, values and well-being of workers (Bentley *et al.*, 2016). In other words, STS states that social and technical systems are interrelated (Trist and Bamforth, 1951) – and thereby helps to understand how people interrelate with technologies such as AI (Makarius *et al.*, 2020).

Building on STS theory, Pasmore *et al.* (2019) proposed a more dynamic framework for STS design, aiming to develop organizations into agile, networked systems that leverage advanced digital technologies. They connected STS and organizational change and called for attention to the role of STS in organizational changes. Their framework includes three levels of design work: (1) work design, (2) operational design and (3) strategic design. These levels collectively strive to balance the technical, social and ecosystem systems, as well as the organization itself.

In terms of *technical systems*, AI technologies now encompass a wide and rapidly growing ecosystem, including general-purpose technologies such as LLMs (ChatGPT, Claude, Copilot) and AI-assisted research tools such as Consensus, Scite, Elicit, Research Rabbit. The *social system* involves leadership and culture (norms, values, identities), whereby the use of AI is changing how academics view their job (Bearman *et al.*, 2022). At the level of *ecosystems*, supranational organizations such as the OECD, UNESCO and the European Union have developed frameworks that recommend and shape how AI is used in the HE context (Miao and Cukurova, 2024; Miao and Holmes, 2023; OECD, 2026). By prioritizing balance and dynamism between these technical, social and environmental components, the future-focused

STS proposed by [Pasmore et al. \(2019\)](#) provides a suitable foundation for understanding and theorizing how a novel and dynamic technology such as AI can be designed and implemented in HE with respect to human agency and collaboration, as well as organizational norms and practices. Accordingly, this paper applies STS theory as a guiding lens to explore the interplay among the work design, operating design and strategic design ([Pasmore et al., 2019](#)), which will be discussed next.

### 2.3 AI and academic work (design)

Because this research set out to study how AI shapes academic work, we first consider the *work design level* ([Pasmore et al., 2019](#)), where specific tasks, roles, processes and expertise required to carry out core academic functions are defined ([Renkema and Tursunbayeva, 2024](#)). In the case of HE, these revolve around teaching, research and service activities ([Rapert et al., 2002](#)), described below, all of which are increasingly affected by AI ([Barros et al., 2023](#); [Bechky and Davis, 2025](#); [Peres et al., 2023](#)).

**2.3.1 AI and teaching activities.** AI is transforming academic teaching by automating administrative tasks, personalizing learning and expanding the time and place of education ([Barros et al., 2023](#)). It supports teachers through automated grading and content creation, providing learning insights and enabling personalized tutoring ([O'Dea, 2024](#)). AI-powered virtual classrooms and global platforms facilitate remote education, though reliance on these tools may require rethinking traditional assessments.

Additionally, AI enables time-independent learning through recorded lectures, chatbots ([Crawford et al., 2024](#)) and automated feedback, helping students learn at their own pace while allowing teachers to manage workloads more efficiently and engage students more effectively ([Huang et al., 2025](#)). While AI enhances teaching, it also raises concerns about academic integrity ([Waqas et al., 2025](#)), pedagogy and the evolving role of educators. The increasing use of AI requires teachers to develop new pedagogical approaches, for example, changing from providing educational content to designing learning experiences (e.g. [Deveci et al., 2025](#)), and warrants specific professional development of teachers as AI is being integrated in educational settings ([Tan et al., 2025](#)).

**2.3.2 AI and research activities.** AI is reshaping research by automating tasks, generating insights ([O'Dea, 2024](#)) and transforming methodologies across disciplines. It aids in research conception, data analysis, literature synthesis and academic writing ([Huang et al., 2025](#); [Kwon, 2025](#)) while fostering new research methods, such as AI-driven pattern discovery and qualitative-quantitative integration. AI-powered tools facilitate literature reviews, coding and statistical analysis, raising debates about their role in knowledge synthesis, knowledge development, knowledge evaluation and knowledge translation ([Grimes et al., 2023](#)), all knowledge work components ([Renkema and Tursunbayeva, 2024](#)).

Virtual and augmented reality expand research environments, enabling global collaboration while revolutionizing qualitative data collection. AI-driven automation also influences research timelines, potentially accelerating publication processes ([Barros et al., 2023](#)) and reshaping academic evaluation ([Bechky and Davis, 2025](#)), while also promising to increase the rigor of research methods ([Grimes et al., 2023](#)). However, its use to monitor researchers' productivity raises ethical concerns about digital surveillance and work-life balance. Moreover, concerns have been raised about the authenticity, transparency and reliability of research, as AI systems are not free of errors and biases (e.g. [Grimes et al., 2023](#)).

**2.3.3 AI and services activities.** AI can also enhance academic service-related activities by automating and streamlining tasks such as mentoring ([Huang et al., 2025](#)), peer review ([Bechky and Davis, 2025](#)), grant applications and administrative duties ([Barros et al., 2023](#)). It supports academics in connecting with industry for research and funding, finding suitable mentors and reviewers and organizing conferences or committee work. AI also helps manage routine tasks such as email sorting, scheduling and expense reporting, allowing scholars to focus on core responsibilities ([Renkema and Tursunbayeva, 2024](#)).

Virtual reality technologies enable remote participation in meetings and conferences, while AI-powered tools assist with language translation and the dissemination of expertise. AI-powered teacher bots can help students to learn (Pillai *et al.*, 2024). Finally, by supporting multitasking, AI can help scholars handle multiple activities simultaneously, increasing efficiency and productivity in academic service roles (Renkema and Tursunbayeva, 2024).

In conclusion, to answer the research question of how AI shapes academic work, we need to consider changes in teaching, research and academic services. Our research framework, therefore, includes these three domains to explore changes and their key drivers.

#### 2.4 Operational and strategic design

Despite the transformative potentials at the work design level, research consistently shows that the impact of technology on work (design) is not predetermined (Parker and Grote, 2022a). Thus, to uncover these key drivers, modern STS theory suggests accounting also for the operational and strategic design levels (Pasmore *et al.*, 2019). For instance, the technological properties of AI – such as algorithms and data architectures – interact in complex ways with human factors, organizational norms and institutional structures. This makes the *operational design level* particularly important, as it captures how organizations make decisions about adopting technology and embedding it in a social system. As such, it is important to study how HE make informed and timely decisions about technology deployment and social system structures, including talent strategies, leadership models and organizational culture (Tierney, 1988).

The *strategic design level* focuses on refining an organization's purpose, governance, ecosystem and capabilities to optimally embed it in the broader environment (Pasmore *et al.*, 2019). Although HE's *organizational purpose* is generally stable, failing to adapt can threaten long-term viability. *Governance* must evolve to reflect stakeholder priorities, necessitating faster and more equitable decision-making processes. The *ecosystem* component underscores that HE institutions do not operate in isolation but rather as nodes within interconnected networks of partners, including industry, government and global academic communities (Leal Filho *et al.*, 2025). Within this broader system, the core (academic) organization plays a central role, acting as the center that coordinates efforts, aligns values and governs interactions. Rather than operating as static structures, these organizations must be designed as what Pasmore *et al.* (2019) describe as adaptive systems or dynamic sociotechnical arrangements capable of continuously adjusting and realigning in response to environmental change.

#### 2.5 Multilevel sociotechnical factors of influence

Combining the previous sections and considering that this study responds to the pressing need for research on HE that simultaneously considers the technical and social dimensions of AI integration, we draw on STS theory to examine the interplay among the work, operating and strategic design levels of HE institutions adapting to AI use. Developing this understanding, institutions can pursue balanced optimization to improve the alignment between the system and the environment, thereby increasing sustainability.

This multilevel perspective builds on insights already emerging from other knowledge-intensive domains – such as the work of Salwei and Carayon (2022) on AI in clinical environments – and aligns with conceptual contributions by Draude *et al.* (2019) and Zhang *et al.* (2025), who advocate for a more integrated, human-algorithm perspective. While these studies have provided novel insights into knowledge-intensive domains, we lack an understanding of how and why AI is shaping academic work. By extending these previous contributions to the context of HE institutions, this study uses STS as a sensitizing framework to empirically explore changes in academic work and develop a comprehensive STS-informed framework for understanding and guiding AI adoption in HE.

### 3. Methodology

We adopted an exploratory qualitative research design, which is particularly well-suited for investigating emerging trends and phenomena around AI (e.g. [Wu et al., 2023](#)). As an innovative data source, we used publicly available podcasts from platforms such as Apple Podcasts and Spotify. The use of archival and secondary sources in qualitative inductive research is increasingly recognized for its potential to generate novel insight ([Brownell et al., 2024](#)). In particular, secondary interviews have been identified as under-valued yet valuable data sources ([Kulkov et al., 2023](#)). Drawing inspiration from [Kulkov and colleagues \(2024\)](#), we found that podcasts offer several advantages, including accessibility, replicability for verification by other researchers and the capacity for rapid data gathering, thereby enhancing the relevance and timeliness of research findings. Our podcast approach captured the perspectives of those at the forefront of this rapidly developing research phenomenon, including edtech experts, academic leaders, investors and educators, providing a suitable sample for this exploratory inquiry ([Brownell et al., 2024](#)).

Moreover, the use of pre-existing data minimized researcher intervention, reducing potential biases and increasing the impartiality of the results ([Thomson, 2022](#)). Nevertheless, we acknowledge that podcast discussions are influenced by the podcast host, guests and intended audience. At the same time, this very weakness can be considered as a strength: podcast hosts often act as well-informed and engaged research assistants, stimulating rich discussions ([Thomson, 2022](#)).

#### 3.1 Data collection

We adopted a thorough systematic approach to collect data for our Podcast analysis. Podcast series and episodes were first searched for by combining the keywords “artificial intelligence,” OR “AI,” AND “Academia” on the specific podcast channels dedicated to technology in education, including EdSurge and Edtech Insiders, both of which are explicitly focused on technology in education and hold recognized positions within the edtech ecosystem. Relevance was initially assessed through episode descriptions and keywords, with selections discussed between both authors. Additional searches by case title and interviewee were conducted on Apple Podcasts and Spotify to expand our sample. Our search strategy yielded 85 episodes, ranging from 6 to 92 min. The selected podcast episodes were transcribed verbatim, after which the authors read and discussed them to determine whether they met our inclusion criteria.

We excluded episodes that were not publicly available, not in English, or that did not focus on the use of AI by academics, such as episodes centered only on AI use in primary or secondary education. Consequently, we included in our analysis only episodes that met the following inclusion criteria: Public Podcasts in English that discussed AI in academic work, which could be either teaching, research or academic services. In doing this, we started the process of engagement with and reflection on our data set ([King and Brooks, 2017](#)). The final sample included for the analysis comprised 66 podcasts posted between November 2017 and July 2023 (see [Supplementary Materials](#) for the list of qualifying Podcast episodes and their main characteristics). The topics of the podcasts were wide-ranging. They explored how AI is transforming education and academia, focusing on its use in research, teaching, assessment and academic integrity. Other key themes include the ethical challenges of AI adoption, the balance between automation and human expertise, and the evolving role of educators.

#### 3.2 Data analysis

We employed template analysis as our approach to make sense of the data ([King and Brooks, 2017](#)). We inserted all transcriptions in Atlas.ti. Before the start of our analysis, we defined a set of broad *a priori* codes ([King and Brooks, 2017](#)) based on dimensions of the future of work (where, when and what) and the categories of academic work (research, teaching and services), reflecting our initial research focus on the application of AI in

academia (Renkema and Tursunbayeva, 2024). To construct the initial coding template, both authors independently coded five medium-length episodes each, using both the *a priori* categories and emergent codes. These initial coding templates were then discussed collaboratively, with first-order codes being organized into meaningful clusters to form a preliminary template.

Next, each author independently coded an additional ten episodes using this updated template, identifying segments of text relevant to the research questions and applying corresponding codes. The resulting analyses were compared and discussed to refine the coding structure – adding new themes, redefining existing ones and merging overlapping categories – leading to the development of a revised template. This revised template, featuring a hierarchical organization of codes, was then applied to another set of 20 episodes and used to re-code the initial episodes. Higher-order themes were elaborated through nested sub-themes, and multiple levels of coding were established – resulting in the final “simplified” template.

After completing these iterations, the authors convened to finalize the template, ensuring it provided a rich and comprehensive representation of the dataset (King and Brooks, 2017). This template was applied to all the remaining episodes. Given the richness of the data, our final template contained a high number of themes. In reporting our findings, we concentrated on the most salient themes relevant to our research questions, and we also explored interrelations between themes, beyond their hierarchical organization. Discussing our insights, we recognized themes that reflected both social and technological dimensions across organizational levels. For instance, the results show that institutional choices and technical developments were often mentioned as shaping factors. Based on these reflections, we decided to adopt the STS theory as a guiding framework for interpreting our findings. For example, inspired by the framework by Pasmore *et al.* (2019), the third-order categories related to the content of academics’ work (teaching, research, services) were clustered as the work design component, while the sociotechnical factors were categorized under operational and strategic design.

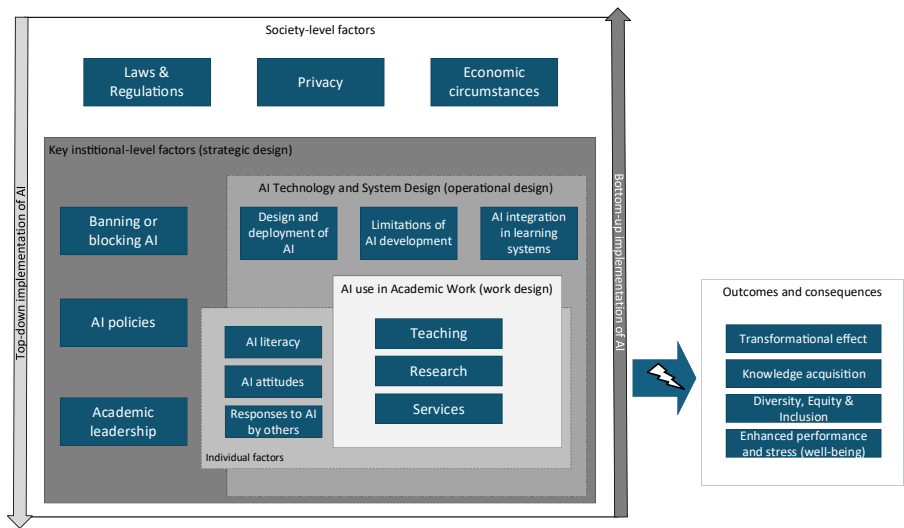
We adhered to most quality assurance procedures recommended by King and Brooks (2017), including independent coding, maintaining an audit trail and providing “thick descriptions” supported by participant quotes (see [Supplementary Materials](#) for an overview of the final data structure and for the empirical evidence with illustrative quotes). In line with standard practices in template analysis, we present our findings according to the main themes identified, illustrating our interpretations with examples drawn from the dataset.

#### 4. Results

The findings highlight that the use of AI has the potential to significantly (re)shape the work of academics. Importantly, and in line with sociotechnical theorizing, we uncovered social and contextual aspects playing important roles in shaping academic practices (see [Supplementary Materials](#) and [Figure 1](#)). The use of AI not only provided new opportunities but also introduced important concerns, highlighting the novel tensions that academics and HE institutions faced with the emergence of AI. Sociotechnical factors such as the developments in AI technologies, institutional policies, national regulations and (cultural) attitudes toward AI in academia were key drivers of the development of AI in academia.

Moreover, we found examples of how AI applications can shape academic practices and transform specific academic activities (see [Supplementary Materials](#) for illustrative quotes based on our template analysis and the categories and dimensions that are used to structure the results). The use of AI has been particularly described in the teaching domain, while research activities were also impacted. Academic services were almost absent from the empirical data, indicating that these activities were not being significantly discussed and/or impacted for now.

We next describe how AI use impacted these aspects of academic work. First, in [section 4.1](#), we describe the influences of AI on the *work design* component of the STS framework as theorized in 2.3. Then, in [section 4.2](#), we describe the *sociotechnical factors* that shape these



**Figure 1.** Sociotechnical AAITF framework of AI-transformation in academia. Source: Authors' own work

influences of AI on the work design of academics – followed by outcomes and consequences in [section 4.3](#). In the Discussion ([Section 5](#)), we link the empirical findings explicitly to the work, operational and strategic design levels as proposed by [Pasmore et al. \(2019\)](#).

4.1 AI use in academic work

4.1.1 *Teaching: AI prompted teachers to rethink existing approaches to education.* The results showed that the use of AI was most evident in education, a domain that is undergoing many changes, forcing academics to change their current approaches to teaching. AI usage changed education in mainly four ways, which we outline next.

First, teaching activities and teachers were *augmented by AI*. Academics and HE institutions adopted and incorporated AI to improve their work, whereby a hybrid model of teacher–AI collaboration emerged. One of the most prevalent changes to education was the personalization of teaching activities. For instance, AI allowed teachers to provide students with tailored approaches and personalized support.

Furthermore, AI was used by teachers to directly generate educational materials such as course and lesson plans, assignments, exam questions, teaching materials and feedback, and thereby functioned indirectly as a teaching assistant providing help to both academics and students:

And AI really can become that assistant, that support for a teacher [...] And it will do things such as helping to grade papers, helping to create lesson plans, helping to scaffold lessons, helping to create materials. (#57)

A very important issue was that teachers grappled with students who increasingly use AI, which forced educators to rethink their assignments and assessments. Finally, AI provided information and suggestions to support decision-making, such as deciding what educational interventions specific students need.

Second, due to the rise of AI usage, discussions emerged around *automation and teacher replacement*. In various episodes, worries were expressed about the potential of AI replacing teaching. However, although some described that AI could replace teachers, others found it more likely that specific teacher activities would be automated. Particularly, AI was seen as

useful for the delegation of tasks, for example, by taking over the boring and repetitive tasks of teachers. These activities were mostly related to administrative requirements.

Third, while distance learning and online training are enabled by digital technologies, AI was reported to enhance these environments through adaptive and intelligent functionalities. Virtual platforms could allow instructors to teach *from anywhere and at anytime*, while AI added capabilities such as chatbots for student support, automated feedback or analytics could personalize learning pathways. Distance learning was reported to now be embedded in traditional courses and expanded through the online massive open courses format, with AI-driven personalization increasingly integrated.

Fourth, the incorporation of AI in education emerged to be complemented by changes in what was being taught. Not only did teachers need to gain *new knowledge and skills* in teaching with AI, but the content of education also changed. It became increasingly important that students know how to work with AI – to gain so-called AI literacy – to prepare them for their work–life where they interact with generative AI:

[My students] are graduating seniors, they are going into sales and recruiting and real estate and nonprofit management. All of those things are going to involve them writing copy and summarizing ideas and putting stuff together for a website. And the truth of this is, this [GenAI] is being used in all those industries already. We're not talking about the future, we're talking about right now. [ . . . ] And so if we are fighting this, or pretending it doesn't exist, we are systematically disadvantaging our students from entering the workforce. (#31)

Furthermore, as AI was reported being increasingly used, student learning changed and different types of knowledge were required from students, such as problem-solving skills and the ethical deployment of AI.

**4.1.2 Research: nascent AI-driven research activities.** Research activities were also impacted by the use of AI – albeit that research was substantially less prominent in the dataset. AI-driven research involved academics' integration of AI-tools as *co-creators* in their work. Beyond (scientific) writing, AI was recognized for its (potential) applications and use in other search activities, such as coding, programming, data analysis for research-related tasks and supporting research to become more open-access.

One thing that it can do is generate text for research papers. So one way is you can feed ChatGPT a prompt and it will generate a pretty coherent and grammatically correct paragraph, or even it can do a full research paper. So of course, we're not going to use ChatGPT to write our research papers, but what it can do, and can be particularly useful, is when you're stuck with a writer's block, or you're stuck on an idea and when you need to quickly generate a rough outline or rough draft of a paper, it can be very useful. (#27)

**4.1.3 Services: the underexplored impact of AI in academic services.** The third core component of the academic job consists of providing academic services, such as supervising and leading, peer-reviewing and academic committee work. However, almost none of these academic services were described in the Podcast episodes. The only related activities involved the *role of (university) administrators*, which is not typically filled by academics, and using AI to *write letters of recommendation* for students.

And [AI] will do things such as . . . helping to write . . . letters of recommendation, helping to analyze financial aid letters, helping to handle all of those different contexts to do it. (#57)

#### 4.2 Sociotechnical factors shaping the adoption of AI in academia

The adoption of AI in academic institutions emerged as largely shaped by drivers operating at different levels. We found that these multilevel sociotechnical drivers existed at the individual,

institutional and societal levels, where these factors either facilitated or hindered the adoption and use of AI.

*4.2.1 Individual differences shaped AI adoption.* At the individual level, we identified three factors that shaped how academics incorporated AI in their work, by affecting their ability and willingness to use AI. First, academics' awareness and understanding of AI affected the (effective) adoption of AI. Faculty members displayed varying levels of *AI literacy*, whereby more advanced knowledge of AI was linked to higher levels of integration. Second, *attitudes* toward AI played an important role. The responses of academics to AI varied substantially, with some being very positive and embracing the technology, while others were reluctant and rejected its use:

Just under four out of 10 teachers are actually allowing their students to use in the classroom. That's a little bit low. So a question, I guess I would have and something to investigate further here is Why is it low right? [...] I wonder if teacher mindset plays a role into this, right? (#45)

Third, the use of AI in academia elicited *diverse responses* from students. Students used AI tools themselves for writing and learning, but concerns were also expressed regarding fairness and transparency about the use of AI by teachers and institutions. For instance, the use of video recording and facial recognition on campus led to worries about privacy and bias.

*4.2.2 Key institutional-level factors shaping AI adoption.* At the institutional level, university policies and administrators played an important role in shaping the work of academics. Developments in AI, and especially the launch of ChatGPT, led to diverse responses from university leaders, which directly impacted the use of AI by academics. Thus, some universities responded by *banning* AI applications such as ChatGPT though after reconsidering their decisions, whereas others continued existing practices.

[...] a big article by New York City chancellors who recently came out and said, Hey, when we initially banned ChatGPT and AI tools in our schools, we were wrong. We shouldn't have done that. (#57)

The developments in AI required academic institutions to adjust and *create AI policies*, rules and guidelines about the use of AI in the classroom and its integration into curricula. For example, universities needed to clarify what teachers and students are allowed to do with AI. *Leadership* from university administrators and their position toward AI also played a pivotal role in shaping AI adoption among academics.

*4.2.3 Society-level factors shaping AI in academia.* National politics and policies emerged as another key driver shaping the future of academic work. Regulation of AI played an important role, next to concerns about data sharing and privacy and economic circumstances such as investments in educational programs and shortages in academic staff.

One of the most important themes emerging from the analysis of the podcasts was the *regulation* of AI in the academic context. As the development and adoption of AI accelerated (e.g. the launch of ChatGPT), calls for specific AI policies became louder.

But the reality is, I would imagine that a lot of ... higher institutions are going to really plan to do some big deep dives on how they allow AI to be used that their institutions, whether their policies bake directly into their codes for misconduct or other things. I think a lot of that work is going to happen during the summer. (#35)

Although banning AI completely was discussed, many experts argued that banning AI was impractical and instead advocated for clear rules/guidelines balancing experimentation with oversights, safeguarding privacy, transparency and authenticity. These discussions were also linked to concerns about educational technology vendors using student data to train AI models.

Concerns about data sharing and *privacy* also emerged as an important societal issue. Experts expressed worries about sensitive student data in learning management systems, facial recognition on campuses and general apprehension about the ethical use of AI in academia.

Finally, *economic circumstances* such as investments in education and shortages in academic staff were identified as important societal drivers. According to some experts, AI was viewed as helpful to address staffing shortages by augmenting and automating academic tasks. However, it was noted that achieving the required substantial investments was not something that all universities could afford.

*4.2.4 Technology-level factors influencing AI adoption.* The final central theme concerned technical aspects related to the design and deployment of AI in academia, limitations of AI and the incorporation of AI into existing learning systems.

Regarding the *design and development requirements* for AI for academic purposes, developers were reported to face numerous choices that could affect use and outcomes – and thereby shape how AI affects academic work. For example, the type of AI used: LLMs, machine-learning prediction models, robotics or GenAI; integration of AI models APIs; grading standards; and choice of cloud providers. Here, we observed a shift in how AI was framed across the podcasts. In the earlier period, AI was discussed primarily in relation to organizational predictive analytics, adaptive learning systems and data-driven decision support. Following the launch of ChatGPT, the discussions shifted toward publicly available GenAI tools.

Secondly, several *limitations of AI-development* were identified, underscoring the need for responsible AI. For example, the data used to train AI education models may not be representative of the population, leading to biased grading results.

So if we don't have extremely representative data that's both representative of large numbers of students in different contexts, but also can be localized to the specific context, then the algorithms are going to produce biased results. (#01)

Moreover, GenAI could make mistakes and produce false information, necessitating critical evaluation of the produced outputs and verification of sources. Finally, vendors of educational software emerged as important actors influencing the work of academics. Providers of learning management systems used by universities increasingly *integrated AI features*, such as AI-chatbots, into their platforms, suggesting that AI is becoming an integral part of academic work regardless of individual awareness or acceptance.

#### *4.3 Outcomes and consequences of AI in academia*

The episodes also highlighted the (un)intended consequences and implications, most notably its transformational effect. One of the critical *transformational* effects concerned changes in knowledge acquisition. Many Podcast guests in our sample believed that AI had changed the value of knowledge and the way learning takes place. On the one hand, *knowledge acquisition* and increasing one's understanding were reported to become AI-mediated with personal assistance, whereas on the other hand, new types of knowledge, such as understanding how to critically interact with AI, were considered more important.

There are also some potential drawbacks, such as promoting an overreliance on AI, [thereby] diminishing critical thinking. And misinformation. Students do not fully engage in the learning process or neglect to develop important problem-solving skills. (#51).

AI was also discussed as a positive force for *diversity and inclusion*. Specifically, AI was seen as beneficial to foster the inclusion of individuals with special needs, such as those who have dyslexia or ADHD. For instance, students with specific needs were reported to benefit from the tailored support of chatbots such as ChatGPT.

... because what I'm excited about, or I feel positive about, is how in many ways ChatGPT for lots of people, that are divergent people, people from marginalized backgrounds and experiences like ChatGPT becomes a really phenomenal code switcher in accessing a lot of the embedded assumptions. (#62)

At the same time, concerns were raised that AI could exacerbate existing inequalities, as AI could incorporate or augment existing biases, and unequal access to technology might unevenly distribute (potential) benefits of using AI.

Finally, although there were positive individual-level outcomes reported from AI use such as *improved learning, efficiency or creativity*, these benefits were reported to be accompanied by increased stress by academics and students, who were already overburdened, and required to adapt to novel technologies.

## 5. Discussion

This study investigated how AI impacts academic work in HE institutions across teaching, research and services. Using qualitative analysis of 66 Podcast episodes with those at the forefront of technological developments and those with expertise in academia, we applied a sociotechnical lens and multilevel perspective to reveal the multifaceted and dynamic nature of AI integration in academia, shedding light on the key drivers that underpin the academic work landscape. This enables us to map how AI is expected to shape the work of academics, provide direction for future research and offer recommendations for practice.

### 5.1 Academic AI-transformation framework (AAITF)

We argue that the adoption, implementation and use of AI, regardless of its type or release, in academia should be considered within the social and technological contexts to understand how AI shapes academics' work. [Figure 1](#) depicts our framework, whereby its main blocks and components are based on the Data Table (See [Supplementary Materials](#)), which also functioned as the structure of the Results section. The sociotechnical framework extends the work design perspective in academia ([Parker and Grote, 2022a](#); [Renkema and Tursunbayeva, 2024](#)), which represents the foundational level comprising the core activities that academics perform, by adding empirically derived factors of influence that shape academic work across multiple organizational levels.

In line with earlier research adopting STS (e.g. [Pasmore et al., 2019](#); [Zhang et al., 2025](#)), our framework also includes the operational systems level, which comprises the technical and social processes, while in line with [Carayon et al. \(2015\)](#), a larger socio-organizational context in our study is represented as higher-level factors surrounding the operational level, including elements of strategic design ([Zhang et al., 2025](#)). These levels and their components will be outlined below, whereby we use the STS lens to reflect on the empirical findings as outlined in the Results section. Specifically, academics' work is linked to the work design component, and the individual differences, institutional-level factors and society-level factors are classified as the sociotechnical factors that shape the work design. Dimensions related to AI technology are categorized as the technical component of STS, while factors in individual differences, institutional-level factors and society-level factors are mainly categorized as social dimensions. Finally, the operational component captures the AI technology, work design and individual differences together, while the strategic component adds key institutional-level factors.

Starting from *work design*, as outlined in the results, our model shows that the adoption and use of AI impacts the three core work activities of academics: teaching, research and academic services ([Rapert et al., 2002](#)) – where it can automate, augment, replace and reconfigure work activities (see [section 4.1](#)) and thereby have a transformational effect on academic work.

Academics themselves utilize the social and technical resources that the adoption and use of AI tools permit, which, as a result, influence their work performance and well-being levels. The AAITF framework suggests that the influence of AI on academic work is shaped by individual-level social factors such as AI skills, attitudes and responses by others. Based on a combination of these factors, we argue that new tensions are likely to emerge [\[1\]](#). Academics are confronted with the AI-usage, AI stimulation and responses by others, such as students and

their institutions, which requires them to adjust and adapt. For instance, AI use was repeatedly associated with an exacerbation of inequalities and biases (see [sections 4.2.1 and 4.3](#)), raising concerns from students and thereby shaping how academics approach AI in their work.

Furthermore, in line with earlier studies (e.g. [Laupichler et al., 2022](#)), our results show that academics' AI skills impact the use of AI in academic work – highlighting the importance of *Individual differences*. The findings show that a shift in expertise is necessary, as academics are required to gain AI-literacy (see [4.2.1](#)), which is described as competencies that enable them to critically use and evaluate AI in their work ([Long and Magerko, 2020; Ng et al., 2021](#)). Finally, our framework indicates that personal attitudes of academics are important factors influencing their use of AI, echoing the findings of [Waqas et al. \(2025\)](#), as results indicated that some embraced AI, whereas others outright rejected it. Hence, because our study shows that AI is both perceived as a helpful tool by some, but also as a trigger for concerns by others, it creates new tensions at the work design level. As a result, academics need to navigate these (potentially) competing demands while crafting their work.

The system design, or *operational design*, involves not just the use of technical systems (LLMs, AI-supported tools), but also developing and incorporating suitable and responsible AI-apps that are integrated into academic work processes and existing ICT systems, such as learning platforms and communication channels (technical systems). For instance, software vendors increasingly integrate AI-features in their existing products (see [4.2.4](#)). These developments are inseparable from the social systems, whereby they change existing relationships and connections. For example, the relationship between academics and students can change when AI automates repetitive tasks, and students use AI as a personal tutor instead of asking their teachers (see [4.1.1](#)). Additionally, as academics use GenAI to support writing or co-creating research (see [4.1.2](#)), the relationship between academics also evolves: AI becomes an academic assistant, which becomes a new collaboration partner. However, these technical and social systems create tensions that need to be balanced ([Zhang et al., 2025](#)), to support both academic performance (efficiency), as well as the well-being of academics and students, and knowledge acquisition and dissemination. Moreover, the results show that limitations of AI should be accounted for to prevent the incorporation of bias ([Baker and Hawn, 2022](#)) and limit the production of erroneous information, also called hallucinations ([Kulkarni et al., 2024](#)).

The *strategic design* involves not only the design of the organization but also the ecosystem, governance, and purpose. In the current context of the AI transformation in academia, this includes the institutional-level and the societal-level factors. Our empirical results highlight that universities and academic leadership play important roles in developing policy and governance structures to incorporate AI in academic practices – some like the New York school system even banning AI tools (see [4.2.2](#)) – thereby co-shaping the adoption of AI in academic work. For example, universities need to navigate the tensions between stimulating AI adoption and thereby potentially enhancing academic work and dealing with the (un)intended consequences for academics, students and knowledge generation. Moreover, the latest developments in GenAI applications enable academics and students alike to adopt advanced technologies and experiment in their own practices without their universities being involved. This so-called bottom-up innovation process (e.g. [Renkema and Bos-Nehles, 2024; Retkowsky et al., 2024](#)) requires universities to respond rapidly with appropriate policies and governance structures, rather than initiating lengthy, top-down change initiatives.

Beyond the institutional-level, national and supranational laws and regulations, societal concerns about privacy and economic circumstances were found to be important sociotechnical factors (as outlined in [Figure 1](#)). We have seen that some countries have prohibited the use of AI in universities (e.g. Italy banned ChatGPT), which shows that national policies directly impact the leeway universities have in adopting AI (see [4.2.3](#)) – underscoring the importance of such policies and guidelines ([Nguyen et al., 2025](#)).

Finally, the framework highlights the multilevel relationships and tensions that emerge between levels. For example, at the meso-level, universities may encourage AI use to increase efficiency, while at the micro-level, some academics feel anxious or concerned about AI.

Furthermore, the individual adoption and experimentation with AI by enthusiastic academics prompts a response whereby institutions develop policy, which in turn shapes the adoption and use of AI. Relatedly, micro-level adoption might be much faster than macro- or meso-level policy changes. All these examples highlight the top-down and bottom-up dynamics (see arrows on the left and right sides of [Figure 1](#)) that are represented by the multilevel nature of our framework.

In sum, applying sociotechnical thinking enabled us to show that AI is framed to influence the work of academics and create novel tensions at and between different levels of analysis. AI shapes the higher education transformation through changes in academics' activities (work design), the design and integration of AI into academic processes (operational design), the organizational choices of academic institutions (strategic design), and is also shaped by individual- and societal-level factors – thereby impacting outcomes such as work performance, knowledge acquisition and diversity and inclusion (right side of [Figure 1](#)). It is important to note that these outcomes are meant as categories, which are not inherently positive or negative, but can manifest in both beneficial or detrimental ways depending on the sociotechnical context.

### 5.2 Theoretical implications

Our STS perspective on AI in academic work offers three theoretical contributions that enrich three existing bodies of literature. First, we contribute to the HE literature by applying the work design approach to academic work in the age of AI. This has led to novel insights, identifying how and why AI alters both the content of academic work (e.g. changes in student assessment) and its social structure (e.g. student–teacher dynamics and AI-as-colleague relationships). Our AAITF framework captures these dynamics, integrating STS theory and work design principles into a multilevel sociotechnical lens to understand both AI benefits – such as enhancing and streamlining activities – and its negative consequences, including diminished learning and increased work pressure ([Izak et al., 2025](#)).

Second, we extend the emerging research on the role of AI in transforming knowledge work and learning in the academic context (e.g. [Kulkarni et al., 2024](#); [Peres et al., 2023](#)), by empirically exploring the factors involved in shaping these changes and showing that a combination of sociotechnical factors is important to integrate to understand these transformations better. Specifically, our contribution lies in integrating multilevel thinking from systems theory with a work design lens to capture the interplay between macro-level strategies (e.g. national policy, institutional governance) and micro-level practices (e.g. individual experimentation with AI tools), revealing a dynamic co-evolutionary process of how AI shapes core academic practices. This extends early studies ([Barros et al., 2023](#); [Renkema and Tursunbayeva, 2024](#)) that overlooked such multilevel dynamics, by showing the importance of organizational design choices (e.g. AI policies and leadership), operational design (e.g. AI design choices and integrations), societal drivers (e.g. influence of laws, privacy concerns and economic circumstances) and individual factors (AI attitudes, skills and responses), that together can shape how AI usage changes academic work.

Third, we advance the work design literature. Our results highlight the contingent nature of AI's impact across domains of academic work, which are differently affected, supporting a nuanced, non-uniform view of academic transformation. In line with contingency theory ([Burton et al., 2006](#)), our study suggests that the consequences of AI usage in academia are shaped by a constellation of sociotechnical factors, including the type of AI, academic leadership and national and institutional policies. We thus advance work design literature by incorporating this multi-contingency view, emphasizing the role of context in shaping the work design of academics and its outcomes ([Parker and Grote, 2022a](#)). Moreover, the results show that there is a need for academics to adapt their work because of bottom-up AI adoption by students and peers. Hereby, this research expands on the notion that job crafting is important

(Parker and Grote, 2022b), by showing how AI shapes the work (design) of academics requires the integration of both top-down and bottom-up perspectives.

### 5.3 Limitations and future research

This study is not without limitations. First, the podcast-based methodology – although innovative – did not allow for follow-up questions or member checking. Although experts and experienced academics were interviewed in the episodes, our research does not provide systematic empirical evidence on the use of AI for different domains, their relative importance, and their consequences. For example, some episodes framed AI as a helpful tool (techno-optimistic), whereas others were more critical. Instead, we were mainly interested in identifying sociotechnical categories informing further studies about the influence of academic AI use. Moreover, some episodes were somewhat speculative about the potential effects of AI use rather than the actual changes. Also, podcast hosts and guests are often early adopters, edtech experts or publicly visible scholars who are more inclined to engage positively with AI. As such, these voices may not fully represent the experiences of overworked or skeptical academics, particularly those facing heavy teaching loads, limited institutional support or implementation fatigue. This bias may tilt the AAITF toward opportunity-oriented narratives, while underrepresenting everyday struggles related to AI adoption, such as learning costs, infrastructural constraints or emotional resistance. Future research could address these limitations through focus groups, Delphi studies or longitudinal ethnographies with academics of various experiences and roles and explore their different perspectives.

Second, the current analysis focused broadly on AI in academia, which means we did not take into account the episodes' context nor the specific AI technologies used. For instance, we did not distinguish between types of AI (e.g. machine learning or GenAI), which could have differential effects on the work of academics. This is because our analytical objective in this study was not to examine the impacts of a specific AI application or generation of tools (e.g. ChatGPT), but rather to identify sociotechnical factors shaping scholars' engagement with AI as a broader class of technologies in academic work. Consequently, we deliberately adopted a technology-agnostic analytical lens, focusing on AI as a family of technologies embedded in academic practices, rather than on individual tools or releases. This approach is consistent with recent scholarship in AI in HE (Engström *et al.*, 2024). Further research should disaggregate these technologies and explore their distinct sociotechnical dynamics. The broad focus of this study means that certain contextual conditions, including power dynamics surrounding Big Tech and the Global South perspective, were not deeply engaged with and warrant future research exploring how AI can create new dependencies and inequalities. At the same time, the breadth of the empirical analysis supports transferability of the findings beyond the podcast context to higher education institutions and knowledge work more generally.

Finally, our data primarily concerned AI in education, which is an important topic (Laupichler *et al.*, 2022), but the consequences for research and academic services also merit attention. Indeed, recent work suggests GenAI could transform the research process (Andersen *et al.*, 2025), highlighting the need for further studies. Also, the near absence of impact on *Academic Services* in the analysis might have been due to discursive selectivity in our data set. Podcast formats and public conversations tend to privilege visible and compelling domains such as teaching, assessment, and student misconduct, while routine and procedural service work remains largely invisible. At the same time, academic services are embedded in highly institutionalized bureaucratic structures, where experimentation with AI is constrained by formal rules, legal accountability, and concerns about legitimacy. For example, the use of AI in the review process has been highly debated in recent publications (Naddaf, 2026). Unlike teaching or research, which are often framed as individual responsibilities, service work also involves collective decision-making and shared accountability, increasing the reputational and ethical risks associated with AI use and discouraging open discussion. This gap may reflect a

temporal lag in adoption, as AI integration typically begins with individual scholarly practices before becoming embedded in institutional routines and administrative infrastructures. The relative emphasis on teaching, compared to research and particularly academic services, reflects the underlying distribution of themes in the empirical material and is therefore interpreted as an empirical finding rather than an analytical imbalance, highlighting how different domains of academic work are currently prioritized in discourse on AI.

#### 5.4 Practical recommendations

First, we observed that institutional and professional policies on AI remain largely unexplored—likely due to the early stage of adoption and the reluctance of some academics to acquaint themselves with AI (Dwivedi *et al.*, 2023). However, given that AI policies are critical factors of strategic design, we recommend more systematic attention toward the institutional and professional governance of AI in academia. Interpreting our empirical results through STS lens (Pasmore *et al.*, 2019), we reveal that academic leaders should take a holistic approach to organizational change, focusing not only on the work processes of academics but particularly on continuously designing and evolving their STS, including operating systems and strategic design, aligning them with the fast AI developments in academia. Insights from our study suggest that these developments lead to novel tensions, which institutions need to respond to, for example, by establishing AI governance committees responsible for offering clear guidelines on the use of AI by academics and students and by investing in academic leadership that supports this transformation.

Second, our results suggest that AI in HE should be viewed as a deeply organizational and social challenge, incorporating social and technical factors. Institutional leaders must design AI policies that are not only technically robust but also ethically grounded and pedagogically aligned. HE institutions can, for example, draw on recent frameworks for the responsible use of AI in education (Chan, 2023) or research (Smith *et al.*, 2026) to develop their AI policies, doing so, HE institutions should organize inclusive dialogues with faculty, students and external stakeholders, including educational technology vendors, to establish a policy framework that includes whether AI use is permitted or prohibited. This framework should operate at the level of specific academic tasks, recognizing that AI might be appropriate in some contexts (e.g. explaining theories) while being inappropriate in others (e.g. peer review).

Finally, we emphasize the importance of training and capacity building. Academic staff and students must develop AI literacy continuously, given that AI technologies develop rapidly. As universities move toward strategic integration of AI, multilevel investments aligned with sociotechnical factors of influence, such as the combination of professional development, training programs and technical infrastructure, will be essential to ensure that the benefits of AI are equitably distributed and ethically grounded.

## 6. Conclusion

AI's transformation of academia is uneven and dynamic, whereby novel tensions between possibilities and challenges emerge, influenced by regulation (institutional) policy, technology and individual preferences. Our sociotechnical, multilevel AAITF framework shows AI should be seen not just as a tool but as a phenomenon redefining academic work. Its integration requires critical reflection and intentional design across strategic, operational and work design levels. HE institutions must invest in AI literacy, responsible use and inclusive policies to encourage a careful, collaborative and context-sensitive adoption to support positive outcomes for academics while safeguarding integrity and values.

### Note

1. These novel tensions are based on our interpretation of the results using STS, and are represented in Figure 1 by the icon of lightning bolt.

## Supplementary material

The supplementary material for this article can be found online.

## References

- Al-Bukhrani, M.A., Alrefaee, Y.M.H. and Tawfik, M. (2025), "Adoption of AI writing tools among academic researchers: a theory of reasoned action approach", *PLoS One*, Vol. 20 No. 1, e0313837, doi: [10.1371/journal.pone.0313837](https://doi.org/10.1371/journal.pone.0313837).
- Andersen, J.P., Degn, L., Fishberg, R., Graversen, E.K., Horbach, S.P.J.M., Schmidt, E.K., Schneider, J.W. and Sørensen, M.P. (2025), "Generative artificial intelligence (GenAI) in the research process – a survey of researchers' practices and perceptions", *Technology in Society*, Vol. 81, 102813, doi: [10.1016/j.techsoc.2025.102813](https://doi.org/10.1016/j.techsoc.2025.102813).
- Appelbaum, S.H. (1997), "Socio-technical systems theory: an intervention strategy for organizational development", *Management Decision*, Vol. 35 No. 6, pp. 452-463, doi: [10.1108/00251749710173823](https://doi.org/10.1108/00251749710173823).
- Baker, R.S. and Hawn, A. (2022), "Algorithmic bias in education", *International Journal of Artificial Intelligence in Education*, Vol. 32 No. 4, pp. 1052-1092, doi: [10.1007/s40593-021-00285-9](https://doi.org/10.1007/s40593-021-00285-9).
- Barros, A., Prasad, A. and Śliwa, M. (2023), "Generative artificial intelligence and academia: implication for research, teaching and service", *Management Learning*, Vol. 54 No. 5, pp. 597-604, doi: [10.1177/13505076231201445](https://doi.org/10.1177/13505076231201445).
- Bearman, M., Ryan, J. and Ajjawi, R. (2022), "Discourses of artificial intelligence in higher education: a critical literature review", *Higher Education*, Vol. 86 No. 2, pp. 369-385, doi: [10.1007/s10734-022-00937-2](https://doi.org/10.1007/s10734-022-00937-2).
- Bechky, B.A. and Davis, G.F. (2025), "Resisting the algorithmic management of science: craft and community after generative AI", *Administrative Science Quarterly*, Vol. 70 No. 1, pp. 1-22, doi: [10.1177/00018392241304403](https://doi.org/10.1177/00018392241304403).
- Bentley, T.A., Teo, S.T., McLeod, L., Tan, F., Bosua, R. and Gloet, M. (2016), "The role of organisational support in teleworker wellbeing: a socio-technical systems approach", *Applied Ergonomics*, Vol. 52, pp. 207-215, doi: [10.1016/j.apergo.2015.07.019](https://doi.org/10.1016/j.apergo.2015.07.019).
- Berente, N., Gu, B., Recker, J. and Santhanam, R. (2021), "Managing artificial intelligence", *MIS Quarterly*, Vol. 45 No. 3, pp. 1433-1450, doi: [10.25300/MISQ/2021/16274](https://doi.org/10.25300/MISQ/2021/16274).
- Brownell, K.M., Cardon, M.S., Bolinger, M.T. and Covin, J.G. (2024), "Choice or chance: how successful entrepreneurs talk about luck", *Journal of Small Business Management*, Vol. 62 No. 3, pp. 1684-1717, doi: [10.1080/00472778.2023.2169703](https://doi.org/10.1080/00472778.2023.2169703).
- Bucaioni, A., Ekedahl, H., Helander, V. and Nguyen, P.T. (2024), "Programming with ChatGPT: how far can we go?", *Machine Learning with Applications*, Vol. 15, 100526, doi: [10.1016/j.mlwa.2024.100526](https://doi.org/10.1016/j.mlwa.2024.100526).
- Burton, R.M., Håkansson, D.D., Eriksen, B. and Snow, C.C. (2006), *Organization Design*, Vol. 6, Springer US, doi: [10.1007/0-387-34173-0](https://doi.org/10.1007/0-387-34173-0).
- Carayon, P., Hancock, P., Leveson, N., Noy, I., Sznalwar, L. and Van Hootegeem, G. (2015), "Advancing a sociotechnical systems approach to workplace safety – developing the conceptual framework", *Ergonomics*, Vol. 58 No. 4, pp. 548-564, doi: [10.1080/00140139.2015.1015623](https://doi.org/10.1080/00140139.2015.1015623).
- Chan, C.K.Y. (2023), "A comprehensive AI policy education framework for university teaching and learning", *International Journal of Educational Technology in Higher Education*, Vol. 20 No. 1, p. 38, doi: [10.1186/s41239-023-00408-3](https://doi.org/10.1186/s41239-023-00408-3).
- Chang, Y., Lee, S., Wong, S.F. and Jeong, S. (2022), "AI-powered learning application use and gratification: an integrative model", *Information Technology and People*, Vol. 35 No. 7, pp. 2115-2139, doi: [10.1108/ITP-09-2020-0632](https://doi.org/10.1108/ITP-09-2020-0632).
- Crawford, J., Allen, K.-A., Pani, B. and Cowling, M. (2024), "When artificial intelligence substitutes humans in higher education: the cost of loneliness, student success, and retention", *Studies in Higher Education*, Vol. 49 No. 5, pp. 883-897, doi: [10.1080/03075079.2024.2326956](https://doi.org/10.1080/03075079.2024.2326956).

- Deveci, M.A., Görmez, Y. and Bardakçı, S. (2025), "Generative artificial intelligence in educational technologies", in Şeker, A. and Yüksek, A.G. (Eds), *Artificial Intelligence: Future Frontiers of Generative AI in Engineering*, Livre de Lyon, Lyon, pp. 233-262.
- Draude, C., Klumbyte, G., Lücking, P. and Treusch, P. (2019), "Situating algorithms: a sociotechnical systemic approach to bias", *Online Information Review*, Vol. 44 No. 2, pp. 325-342, doi: [10.1108/OIR-10-2018-0332](https://doi.org/10.1108/OIR-10-2018-0332).
- Dwivedi, Y.K., Kshetri, N., Hughes, L., Slade, E.L., Jeyaraj, A., Kar, A.K., Baabdullah, A.M., Koohang, A., Raghavan, V., Ahuja, M., Albanna, H., Albashrawi, M.A., Al-Busaidi, A.S., Balakrishnan, J., Barlette, Y., Basu, S., Bose, I., Brooks, L., Buhalis, D., Carter, L., Chowdhury, S., Crick, T., Cunningham, S.W., Davies, G.H., Davison, R.M., Dé, R., Dennehy, D., Duan, Y., Dubey, R., Dwivedi, R., Edwards, J.S., Flavián, C., Gauld, R., Grover, V., Hu, M.C., Janssen, M., Jones, P., Junglas, I., Khorana, S., Kraus, S., Larsen, K.R., Latreille, P., Laumer, S., Malik, F.T., Mardani, A., Mariani, M., Mithas, S., Mogaji, E., Nord, J.H., O'Connor, S., Okumus, F., Pagani, M., Pandey, N., Papagiannidis, S., Pappas, I.O., Pathak, N., Pries-Heje, J., Raman, R., Rana, N.P., Rehm, S.V., Ribeiro-Navarrete, S., Richter, A., Rowe, F., Sarker, S., Stahl, B.C., Tiwari, M.K., van der Aalst, W., Venkatesh, V., Viglia, G., Wade, M., Walton, P., Wirtz, J. and Wright, R. (2023), "Opinion paper: 'so what if ChatGPT wrote it?' multidisciplinary perspectives on opportunities, challenges and implications of generative conversational AI for research, practice and policy", *International Journal of Information Management*, Vol. 71, 102642, doi: [10.1016/j.ijinfomgt.2023.102642](https://doi.org/10.1016/j.ijinfomgt.2023.102642).
- Engström, A., Pittino, D., Mohlin, A., Johansson, A. and Edh Mirzaei, N. (2024), "Artificial intelligence and work transformations: integrating sensemaking and workplace learning perspectives", *Information Technology and People*, Vol. 37 No. 7, pp. 2441-2461, doi: [10.1108/ITP-01-2023-0048](https://doi.org/10.1108/ITP-01-2023-0048).
- Gao, C.A., Howard, F.M., Markov, N.S., Dyer, E.C., Ramesh, S., Luo, Y. and Pearson, A.T. (2023), "Comparing scientific abstracts generated by ChatGPT to real abstracts with detectors and blinded human reviewers", *npj Digital Medicine*, Vol. 6 No. 1, pp. 1-5, doi: [10.1038/s41746-023-00819-6](https://doi.org/10.1038/s41746-023-00819-6).
- Grimes, M., Von Krogh, G., Feuerriegel, S., Rink, F. and Gruber, M. (2023), "From scarcity to abundance: scholars and scholarship in an age of generative artificial intelligence", *Academy of Management Journal*, Vol. 66 No. 6, pp. 1617-1624, doi: [10.5465/amj.2023.4006](https://doi.org/10.5465/amj.2023.4006).
- Hryciyshyn, A. and Eassom, H. (2025), "Explaining AI: an AI study by Wiley".
- Huang, Y., Li, S. and Liu, Z. (2025), "Can GenAI complement supervisor support in shaping postgraduates' research experiences? A mixed-methods approach", *Studies in Higher Education*, Vol. 51 No. 4, pp. 1-19, doi: [10.1080/03075079.2025.2495710](https://doi.org/10.1080/03075079.2025.2495710).
- Izak, M., Barros, A., Prasad, A. and Śliwa, M. (2025), "Generative artificial intelligence and learning: at the dawn of idiocracy?", *Management Learning*, Vol. 56 No. 3, pp. 407-415, doi: [10.1177/13505076251348575](https://doi.org/10.1177/13505076251348575).
- Kacena, M.A., Plotkin, L.I. and Fehrenbacher, J.C. (2024), "The use of artificial intelligence in writing scientific review articles", *Current Osteoporosis Reports*, Vol. 22 No. 1, pp. 115-121, doi: [10.1007/s11914-023-00852-0](https://doi.org/10.1007/s11914-023-00852-0).
- King, N. and Brooks, J.M. (2017), *Template Analysis for Business and Management Students*, SAGE Publications, 1 Oliver's Yard, 55 City Road London EC1Y 1SP, doi: [10.4135/9781473983304](https://doi.org/10.4135/9781473983304).
- Klein, K.J. and Kozlowski, S.W.J. (2000), "From micro to meso: critical steps in conceptualizing and conducting multilevel research", *Organizational Research Methods*, Vol. 3 No. 3, pp. 211-236, doi: [10.1177/109442810033001](https://doi.org/10.1177/109442810033001).
- Kulkarni, M., Mantere, S., Vaara, E., Van Den Broek, E., Pachidi, S., Glaser, V.L., Gehman, J., Petriglieri, G., Lindebaum, D., Cameron, L.D., Rahman, H.A., Islam, G. and Greenwood, M. (2024), "The future of research in an artificial intelligence-driven world", *Journal of Management Inquiry*, Vol. 33 No. 3, pp. 207-229, doi: [10.1177/10564926231219622](https://doi.org/10.1177/10564926231219622).
- Kulkov, I., Kulkova, J., Leone, D., Rohrbeck, R. and Menvielle, L. (2023), "Stand-alone or run together: artificial intelligence as an enabler for other technologies", *International Journal of Entrepreneurial Behavior and Research*, Vol. 30 No. 8, pp. 2082-2105, doi: [10.1108/IJEBR-02-2023-0169](https://doi.org/10.1108/IJEBR-02-2023-0169).

- Kulkov, I., Kulkova, J., Rohrbeck, R. and Menvielle, L. (2024), "Leveraging podcasts as academic resources: a seven-step methodological guide", *International Journal of Qualitative Methods*, Vol. 23, 16094069241266197, doi: [10.1177/16094069241266197](https://doi.org/10.1177/16094069241266197).
- Kwon, D. (2025), "Science sleuths flag hundreds of papers that use AI without disclosing it", *Nature*, Vol. 641 No. 8062, pp. 290-291, doi: [10.1038/d41586-025-01180-2](https://doi.org/10.1038/d41586-025-01180-2).
- Laupichler, M.C., Aster, A., Schirch, J. and Raupach, T. (2022), "Artificial intelligence literacy in higher and adult education: a scoping literature review", *Computers and Education: Artificial Intelligence*, Vol. 3, 100101, doi: [10.1016/j.caeai.2022.100101](https://doi.org/10.1016/j.caeai.2022.100101).
- Leal Filho, W., Sigahi, T.F.A.C., Anholon, R., Rebelatto, B.G., Schmidt-Ross, I., Hensel-Börner, S., Franco, D., Treacy, T. and Brandli, L.L. (2025), "Promoting sustainable development via stakeholder engagement in higher education", *Environmental Sciences Europe*, Vol. 37 No. 1, p. 64, doi: [10.1186/s12302-025-01101-0](https://doi.org/10.1186/s12302-025-01101-0).
- Long, D. and Magerko, B. (2020), "What is AI literacy? Competencies and design considerations", *Proceedings of the 2020 CHI Conference on Human Factors in Computing Systems*, presented at the CHI '20: CHI Conference on Human Factors in Computing Systems, ACM, Honolulu HI USA, pp. 1-16, doi: [10.1145/3313831.3376727](https://doi.org/10.1145/3313831.3376727).
- Makarius, E.E., Mukherjee, D., Fox, J.D. and Fox, A.K. (2020), "Rising with the machines: a sociotechnical framework for bringing artificial intelligence into the organization", *Journal of Business Research*, Vol. 120, pp. 262-273, doi: [10.1016/j.jbusres.2020.07.045](https://doi.org/10.1016/j.jbusres.2020.07.045).
- Miao, F. and Cukurova, M. (2024), *AI Competency Framework for Teachers*, UNESCO, doi: [10.54675/ZJTE2084](https://doi.org/10.54675/ZJTE2084).
- Miao, F. and Holmes, W. (2023), *Guidance for Generative AI in Education and Research*, UNESCO, doi: [10.54675/EWZM9535](https://doi.org/10.54675/EWZM9535).
- Naddaf, M. (2026), "More than half of researchers now use AI for peer review — often against guidance", *Nature*, Vol. 649 No. 8096, pp. 273-274, doi: [10.1038/d41586-025-04066-5](https://doi.org/10.1038/d41586-025-04066-5).
- Ng, D.T.K., Leung, J.K.L., Chu, S.K.W. and Qiao, M.S. (2021), "Conceptualizing AI literacy: an exploratory review", *Computers and Education: Artificial Intelligence*, Vol. 2, 100041, doi: [10.1016/j.caeai.2021.100041](https://doi.org/10.1016/j.caeai.2021.100041).
- Nguyen, A., Kishore, S., Hong, Y., Qutab, S. and Dang, B. (2025), "Generative artificial intelligence (AI) in education: from organizing visions to official guidelines", *Information Technology and People*, Vol. 38 No. 8, pp. 172-199, doi: [10.1108/ITP-08-2024-1026](https://doi.org/10.1108/ITP-08-2024-1026).
- OECD (2026), *OECD Digital Education Outlook 2026: Exploring Effective Uses of Generative AI in Education*, OECD Publishing, doi: [10.1787/062a7394-en](https://doi.org/10.1787/062a7394-en).
- Orlikowski, W.J. and Scott, S.V. (2023), "The digital undertow and institutional displacement: a sociomaterial approach", *Organization Theory*, Vol. 4 No. 2, 26317877231180898, doi: [10.1177/26317877231180898](https://doi.org/10.1177/26317877231180898).
- Owens, B. (2023), "How nature readers are using ChatGPT", *Nature*, Vol. 615 No. 7950, p. 20, doi: [10.1038/d41586-023-00500-8](https://doi.org/10.1038/d41586-023-00500-8).
- O'Dea, X. (2024), "Generative AI: is it a paradigm shift for higher education?", *Studies in Higher Education*, Vol. 49 No. 5, pp. 811-816, doi: [10.1080/03075079.2024.2332944](https://doi.org/10.1080/03075079.2024.2332944).
- Parker, S.K. (2014), "Beyond motivation: job and work design for development, health, ambidexterity, and more", *Annual Review of Psychology*, Vol. 65 No. 1, pp. 661-691, doi: [10.1146/annurev-psych-010213-115208](https://doi.org/10.1146/annurev-psych-010213-115208).
- Parker, S.K. and Grote, G. (2022a), "Automation, algorithms, and beyond: why work design matters more than ever in a digital world", *Applied Psychology*, Vol. 71 No. 4, pp. 1171-1204, doi: [10.1111/apps.12241](https://doi.org/10.1111/apps.12241).
- Parker, S.K. and Grote, G. (2022b), "More than 'more than ever': revisiting a work design and sociotechnical perspective on digital technologies", *Applied Psychology*, Vol. 71 No. 4, pp. 1215-1223, doi: [10.1111/apps.12425](https://doi.org/10.1111/apps.12425).

- Pasmore, W., Winby, S., Mohrman, S.A. and Vanasse, R. (2019), "Reflections: sociotechnical systems design and organization change", *Journal of Change Management*, Vol. 19 No. 2, pp. 67-85, doi: [10.1080/14697017.2018.1553761](https://doi.org/10.1080/14697017.2018.1553761).
- Peres, R., Schreier, M., Schweidel, D. and Sorescu, A. (2023), "On ChatGPT and beyond: how generative artificial intelligence may affect research, teaching, and practice", *International Journal of Research in Marketing*, Vol. 40 No. 2, pp. 269-275, doi: [10.1016/j.ijresmar.2023.03.001](https://doi.org/10.1016/j.ijresmar.2023.03.001).
- Pillai, R., Sivathanu, B., Metri, B. and Kaushik, N. (2024), "Students' adoption of AI-based teacher-bots (T-bots) for learning in higher education", *Information Technology and People*, Vol. 37 No. 1, pp. 328-355, doi: [10.1108/ITP-02-2021-0152](https://doi.org/10.1108/ITP-02-2021-0152).
- Rapert, M.I., Kurtz, D.L. and Smith, S. (2002), "Beyond the core triad: just what do marketing academics do outside of teaching, research, and service?", *Journal of Marketing Education*, Vol. 24 No. 2, pp. 161-167, doi: [10.1177/0273475302242009](https://doi.org/10.1177/0273475302242009).
- Rashidov, A. (2024), "Expert algorithm to optimize the process of selecting a topic for a research project with the assistance of ChatGPT", *2024 International Congress on Human-Computer Interaction, Optimization and Robotic Applications (HORA), presented at the 2024 International Congress on Human-Computer Interaction, Optimization and Robotic Applications (HORA)*, pp. 1-5, doi: [10.1109/HORA61326.2024.10550536](https://doi.org/10.1109/HORA61326.2024.10550536).
- Renkema, M. and Bos-Nehles, A. (2024), "The implementation of bottom-up innovation in a formalized context: a resource-mobilization perspective", *Creativity and Innovation Management*, Vol. 33 No. 4, pp. 639-653, doi: [10.1111/caim.12607](https://doi.org/10.1111/caim.12607).
- Renkema, M. and Tursunbayeva, A. (2024), "The future of work of academics in the age of artificial intelligence: state-of-the-art and a research roadmap", *Futures*, Vol. 163, 103453, doi: [10.1016/j.futures.2024.103453](https://doi.org/10.1016/j.futures.2024.103453).
- Retkowsky, J., Hafermalz, E. and Huysman, M. (2024), "Managing a ChatGPT-empowered workforce: understanding its affordances and side effects", *Business Horizons*, Vol. 67 No. 5, pp. 511-523, doi: [10.1016/j.bushor.2024.04.009](https://doi.org/10.1016/j.bushor.2024.04.009).
- Salwei, M.E. and Carayon, P. (2022), "A sociotechnical systems framework for the application of artificial intelligence in health care delivery", *Journal of Cognitive Engineering and Decision Making*, Vol. 16 No. 4, pp. 194-206, doi: [10.1177/15553434221097357](https://doi.org/10.1177/15553434221097357).
- Smith, S.M., Tate, M., Freeman, K., Walsh, A., Ballsun-Stanton, B. and Lane, M. (2026), "A university framework for the responsible use of generative AI in research", *Journal of Higher Education Policy and Management*, Vol. 48 No. 1, pp. 17-36, doi: [10.1080/1360080X.2025.2509187](https://doi.org/10.1080/1360080X.2025.2509187).
- Strzelecki, A., Cicha, K., Rizun, M. and Rutecka, P. (2024), "Acceptance and use of ChatGPT in the academic community", *Education and Information Technologies*, Vol. 29 No. 17, pp. 22943-22968, doi: [10.1007/s10639-024-12765-1](https://doi.org/10.1007/s10639-024-12765-1).
- Tan, X., Cheng, G. and Ling, M.H. (2025), "Artificial intelligence in teaching and teacher professional development: a systematic review", *Computers and Education: Artificial Intelligence*, Vol. 8, 100355, doi: [10.1016/j.caeai.2024.100355](https://doi.org/10.1016/j.caeai.2024.100355).
- Thomson, L. (2022), "Leveraging the value from digitalization: a business model exploration of new technology-based firms in vertical farming", *Journal of Manufacturing Technology Management*, Vol. 33 No. 9, pp. 88-107, doi: [10.1108/JMTM-10-2021-0422](https://doi.org/10.1108/JMTM-10-2021-0422).
- Tierney, W.G. (1988), "Organizational culture in higher education: defining the essentials", *The Journal of Higher Education*, Vol. 59 No. 1, p. 2, doi: [10.2307/1981868](https://doi.org/10.2307/1981868).
- Trist, E.L. and Bamforth, K.W. (1951), "Some social and psychological consequences of the longwall method of coal-getting: an examination of the psychological situation and defences of a work group in relation to the social structure and technological content of the work system", *Human Relations*, Vol. 4 No. 1, pp. 3-38, doi: [10.1177/001872675100400101](https://doi.org/10.1177/001872675100400101).
- Wang, S., Wang, F., Zhu, Z., Wang, J., Tran, T. and Du, Z. (2024), "Artificial intelligence in education: a systematic literature review", *Expert Systems with Applications*, Vol. 252, 124167, doi: [10.1016/j.eswa.2024.124167](https://doi.org/10.1016/j.eswa.2024.124167).

- 
- Waqas, M., Hania, A. and Chunyan, X.U. (2025), "Understanding Aigiarism in higher education: the lens of general AI attitudes and moral disengagement", *Studies in Higher Education*, Vol. 51 No. 4, pp. 1-17, doi: [10.1080/03075079.2025.2497479](https://doi.org/10.1080/03075079.2025.2497479).
- Winn, Z. (2024), *Need a Research Hypothesis? Ask AI*, MIT News | Massachusetts Institute of Technology, 19 December, available at: <https://news.mit.edu/2024/need-research-hypothesis-ask-ai-1219> (accessed 12 July 2025).
- Wu, X., Liu, Q., Qu, H. and Wang, J. (2023), "The effect of algorithmic management and workers' coping behavior: an exploratory qualitative research of Chinese food-delivery platform", *Tourism Management*, Vol. 96, 104716, doi: [10.1016/j.tourman.2022.104716](https://doi.org/10.1016/j.tourman.2022.104716).
- Zawacki-Richter, O., Marín, V.I., Bond, M. and Gouverneur, F. (2019), "Systematic review of research on artificial intelligence applications in higher education – where are the educators?", *International Journal of Educational Technology in Higher Education*, Vol. 16 No. 1, p. 39, doi: [10.1186/s41239-019-0171-0](https://doi.org/10.1186/s41239-019-0171-0).
- Zhang, P., Dillard, N. and Cavallo, T. (2025), "Navigating the limitations of algorithmic management: an integrative framework of sociotechnical systems theory (STS) and strategic HRD", *Human Resource Development Review*, Vol. 24 No. 3, 15344843251320252, doi: [10.1177/15344843251320252](https://doi.org/10.1177/15344843251320252).

**Corresponding author**

Aizhan Tursunbayeva can be contacted at: [a.tursunbayeva@uniparthenope.it](mailto:a.tursunbayeva@uniparthenope.it)