Educational AI

A Critical Exploration of Layers of Production and Productivity

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Abstract

Regarding possible implications for teaching and learning, the article explores the production and productive effects of educational AI from sociology of knowledge/of technology perspectives from three sides: Firstly, the role of knowledge (re-)construction in the creation of educational AI is investigated. In this context, contrasting engineering-oriented approaches, educational AI systems are conceptualised as agentic entities infused with tacit and explicit knowledge about sociality and education, and as potentially reshaping both educational practices and scientific concepts. Looking at promotional and engineering-oriented AI discourses, the article secondly examines how education and AI are linked and how the knowledge pervasion of educational AI is addressed. Findings indicate that the discursive production of educational AI relates to the interwoven assumptions that education and specifically lifelong learning are obliged and able to remedy large-scale societal challenges and that educational AI can leverage this potential. They also indicate that an educational AI system's knowledge is deemed a reflection of explicit (expert) knowledge that in the form of rationales can, in turn, be reflected to the systems' users. Thirdly, regarding arising challenges for the sensitive area of education, educational AI's role in knowledge gathering practices both in educational research and big educational data analysis is addressed.

Introduction

Educational technology based on techniques named artificial intelligence (AI) is increasingly promoted and deployed. Governments and companies, especially big technology firms like Facebook, Google, Amazon or Microsoft, appear to see unlimited potential in AI, and steadily elevate their sponsorship and investments (cp. Hall/Pesenti 2017: 38–39). At present, many stakeholders who equip their educational services and products with AI seem to come from the private sector. However, more extensive use by public educational institutions becomes imaginable, should concepts that deem AI a useful educational, societal, and economic resource enter mainstream education programmes.

DOI 10.14361/dcs-2018-0106

The consequences of broader dissemination affect educational practices and educational knowledge production alike. Contrasting expectations of wide-ranging societal and educational effects of the distribution of AI techniques in education, the recent literature reflects on the issue mostly from short-ranged application-oriented or method-oriented viewpoints. For instance, studies present results of AI-driven educational research (cp. e.g., Brooks et al. 2014) or investigate questions concerning the effectiveness of specific applications (cp. e.g., van der Spek et al. 2013). From a sociological perspective on educational technology, this current state of research is unsatisfactory.

This article approaches the phenomenon from a view that sees the educational relevance of AI as rooted in AI's characteristics as software. Software can be described as to have "become our interface to the world, to others, to our memory and our imagination – a universal engine on which the world runs" (Manovich 2013: 2). Software studies seek to "investigate the role of software in contemporary culture, and the cultural and social forces that are shaping the development of software itself" (ibid: 10). In this paper, the software studies approach of Williamson (cp. 2015a), who examined governing aspects of educationally used software, is incorporated. Educational AI is thus framed as inhering a socially, economically, politically and culturally productive power (cp. ibid: 85) that adds to the mere technical functions of AI-driven systems. According to a Latourian view of symmetrical anthropology, and following a praxeological understanding of the social (cp. e.g., Latour 2007), educational AI can be seen as being capable of shaping and governing practices and subjectivities within education and educational research. Equally, AI systems and the notion of educationally applied AI can be viewed as a result of social, economic, political and cultural production processes (Williamson 2015a: 85), including practices, structures and discourses interlinking education, educational technology and the notion of AI.

The production and productivity of educational AI should in this context be understood as deeply entangled with the tendency to "datafy" and turn into algorithms all kinds of everyday life aspects. There is a relatively thin corpus of works which critically reflect recent data- and algorithm-related developments in education (cp., e.g., Allert/Richter 2017; Williamson 2015a, 2015b). If at all, these works address the topic of AI as an aside. In exploring what are production factors and productive effects of educational AI from a sociology of knowledge perspective on educational technology, and eventually formulating the notion of educational AI accordingly, this article seeks to complement the efforts of these works by drawing attention to some peculiarities of educational AI.

The article is organised as follows: Chapter two briefly outlines techniques that from an engineering point of view seem of importance for AI-driven educational technology. Furthermore, it indicates why plainly adopting the term AI would be problematic for this article's approach of investigating educational AI. Chapter three presents current applications of educational AI and categorises them into four different types of purposes. The main chapter four explores production factors of educationally applied AI and asks in which ways the notion can be assumed to be productive itself. Chapter five summarizes the findings.

Artificial Intelligence: Techniques and Terminology

Today's educational technology tends to make mainly use of the following AI engineering techniques: machine learning, natural language procession, software agents, searching and planning. Additionally, many educational uses of AI rely on so-called knowledge engineering. It accounts for the design of a knowledge structure that is thought to be a formalised ontological reflection of the portion of the world that is deemed relevant for the particular technical application, and its computerization (Davis et al. 1993). The immensely popular AI technique called *machine learning* refers to AI systems that can reconfigure their skills (e. g., identifying students according to their learning style or clustering adult learners to predict retention and dropout risk) with the help of data. The data can, for instance, be previously categorised data (which leads to so-called supervised learning) or not categorised data (which leads to so-called unsupervised learning) (cp. Franklin 2014: 26). *Natural language procession* refers to the computational creation or processing of natural language, mostly in the form of text (cp. ibid). In education, the procession of such sequences of natural language can serve for a variety of purposes: answer recognition, analysis and grading of written text and, where applicable, spoken word, the creation of study material, and the production of supportive text or speech (e. g., for purposes of motivation, explanation, feedback or input request). AI systems which are supposed to sense their surroundings and act upon them autonomously are labelled software agents. Concerning educational contexts, they are used within intelligent tutoring systems (cp. ibid: 27), collaborative learning environments and serious games[1] to create entities (e. g., a tutor or a gaming environment) that behave in ways deemed educationally intelligent. *AI search techniques* play a relevant role in pattern finding (cp. ibid: 25). For example, they could find patterns of effective sequences of training tasks according to specified learner types. AI search techniques often coincide with machine learning techniques. Lastly, *AI Planners* solve complex planning tasks, whereby they aim at finding an optimal path to a predefined goal state (cp. ibid). Within educational contexts, this could, e. g., be utilised for planning the path of a character within a serious game.

In engineering contexts, the term AI is usually used affirmatively. However, regarding the article's endeavour of exploring the production and productive effects of educational AI from a sociology of educational technology point of view,

1 Serious games are digital educational games which can prove useful in situations where, for instance, the learners' exposure to the actual situation they are trained to master might be too expensive or too dangerous (cp. De Gloria et al. 2015: 638–639).

the plain adoption of the outlined terminology turns out unfruitful. This is due to, at least, three problems: The first problem is that definition approaches which refer to the term AI ground in the notion of intelligence. However, to being able to support the investigation of socially intertwined production processes and productive effects of AI-driven educational technology, the notion of intelligence is too limited, if not to the concept of cognition, then certainly to a restricted grasp of the social which is due to the concept's identification of intelligence with capacities tied to one individual entity[2]. Hence, the limited range of sociality the concept focuses contradicts the very nature of a sociologically accentuated exploration. The second problem emerges in the lack of a universally applicable definition of intelligence. An enquiry found more than seventy definitions (cp. Legg/Hutter 2007: 17). Hence, it is anything but obvious what characteristics render an entity intelligent. According to Woolgar, sociological enquiries of the AI phenomenon must be aware of this "interpretative flexibility of notions of 'intelligence'" (Woolgar 1985: 565) or they will be incapacitated due to having "to wait upon the outcome of what (currently) seems an interminable research 'progression'" (ibid). The third problem refers to the dualistic division inherent to the concept of AI that distinguishes between artificial and human. With its focus on differences between entities, the concept obscures that multiple actors different in nature, including actors labelled AI, usually constitute powerful doings, such as aerial warfare, granting loans, performing surgeries or election campaigning, jointly. Similarly, teaching and learning can be described as involving different types of actors.

However, in the present case, the expression AI was used pragmatically: The term guided the author's initial search for applications of educational AI and scientific and promotional texts linking AI and education. Furthermore, regarding vocabulary in this text, terms like AI, AI-driven systems, etc. will denominate the explored phenomena which throughout chapters four and five will successively be reframed and reformulated.

Educational Applications of Artificial Intelligence: an Overview

Having addressed terminological questions, this chapter will outline some examples of educational applications of AI, categorised into four types of purposes: the analysis of educational data to fulfill research tasks (academic analytics) (1), the study of data to inform and govern practices of teaching and learning (learning analytics) (2), the production of entities deemed capable of performing pedagogically meaningful acts (3), and the provision of learning resources (4). The present chapter describes each category briefly to provide the reader with details about the

2 This is on condition that the notion of intelligentsia, which understands intelligence as collective, plays no significant role in concepts of intelligence dealing with AI.

current state of educational AI and establish the basis for the analysis following in chapter four.

Many educational applications of AI closely link to two broader trends, referred to as academic analytics and learning analytics. Both rely on methods for (big) data analysis to investigate educational phenomena – academic analytics concerning academic research, learning analytics concerning real-time teaching/learning processes (cp. Ifenthaler 2015: 448). In *academic analytics* (1), applications of AI serve to perform clustering/modelling, prediction and optimization tasks to explore educational phenomena. An example is a study of Brooks et al. (2014) which aimed at the typification of a specific educational phenomenon. In detail, the authors focused on the investigation of viewership patterns of science students who had access to video recordings of attended face-to-face lectures, and the correlation of such patterns with the students' academic performance (cp. ibid: 282–283). The study used an unsupervised machine learning technique, meaning that the clustering of viewership patterns was not done deductively from previously clustered (and thus somehow theorised) training data. Instead, a *k*-means clustering algorithm was applied, which achieves the formation of an already defined number of clusters by ad hoc clustering gathered data.

Regarding *learning analytics* (2), applications of AI perform assessments of specific aspects of the digitally supported learning process (such as performance, temporal structures, dropout rates, learning strategies or collaboration processes). Applications of learning analytics that make use of AI, entail, for example, automated essay scoring (AES) or adaptive questioning in learning software. An example is MIT's and Harvard's massive open online courses (MOOC) platform edX which in 2013 began to make use of an in-house designed automated essay scoring system (AES), which also was made available for free to anyone (cp. Markoff 2013). AES involves, in each case, a set of customised computerised language analysis techniques (some of them utilizing methods that are labelled AI) to rate the quality of a variety of essay features to predict how humans would typically grade the assignment (cp. Balfour 2013: 41–42). A couple of institutions of higher education, mainly situated in the Anglophone world (AES is currently most applicable to English texts written by native speakers), have already followed this trend, such as the University of Michigan. Since 2017, the institution applies automated text analysis with the help of which it aims to assess which students might need additional support (cp. Brown 2017).

AI-driven learning analytics can also be a foundational part of other educational applications of AI. Those exploit vast amounts of (possibly AI-analysed) data to *create agentic entities* (3) (a tutor, a game character, a learning environment) which are, for instance, employed in serious games, intelligent tutoring systems, and environments for collaborative learning. Another increasingly important type of such entities are entities like Apple's Siri or IBM's Watson whose intended purposes of use include educational use only as one of many others. In any case, such AI-driven entities *are supposed to behave in ways deemed educationally capable,* without a given script, and only with the help of the user's input and an implemented knowledge structure, which contains an idealised and simplified model of the segment of the world relevant for the application's purpose.

Subsequently, I want to detail two forms of such educational AI-driven entities. Within serious games or digital learning environments, AI can create non-player characters. In this case, AI real-time scripts the interactions of non-learner characters with the learner according to the learner's actual actions in the application or contributes to instantaneous adjustments of the game environment. AI accounts for the adaptivity of the game which in turn is assumed to contribute to the improvement of its learning component (cp. Ravyse et al. 2017: 50). Another example less typical is AI-driven applications targeting behaviour and habit change, adherence or management in an educative manner. This applies to popular apps and gadgets targeting physical exercise and diet as well as to applications that attempt to track and govern individual learning processes. Currently, the use of AI techniques for the latter is still quite rare. A recent example of the connection of self-tracking and AI in education is University of Michigan's "Ecoach" (University of Michigan, undated), a behavioural science based web tool facilitating the self-tracking and self-management of study activities for students. To this end, the tool aims at supplying educational support for the students through automatically generated text messages, which can be of suggesting, informative, cautionary or motivational nature, and "normative data visualizations" (ibid).

A fourth type is the *usage of AI as a learning object* (4) or as a *means to create learning objects* like, for instance, videos in surgical training (cp. e.g., Hashimoto et al. 2017: 171). This kind of use occurs mostly in the education of science, mathematics, engineering, and computer science (cp. e.g., Garrido 2012) but it might also be of growing relevance in the humanities and social sciences. As Porayska-Pomsta (2016) suggests, the methodology of AI techniques of so-called knowledge representation and elicitation could, for instance, function as "conceptual tools that can serve to externalise and systematise educators' knowledge in a guided way" (Porayska-Pomsta 2016: 696).

Production Factors and Productive Effects of Educational AI Explored

Having outlined current applications of AI in educational contexts, this chapter proceeds to explore production factors and productive effects of educational AI exemplarily. It will do so by firstly introducing two discursive conjectures about how AI and education link. Secondly, the role of knowledge production in the creation of applications of educational AI is examined. Thirdly, the chapter investigates the way in which the knowledge pervasion of educational AI is addressed in the promotional discourse and draws conclusions concerning learning and teaching. The last part reflects educational AI as a means of producing governing and scientific knowledge.

Educational AI as a Remedy for Large-Scale Societal Challenges

This section will show that the discursive production of educational AI is related to the conjecture that education and particularly *AI-driven education* can solve two major societal problems: educational inequality and the societal upheavals supposedly following the introduction of AI into the working world. To this end, I will describe and examine two instructive figures from the promotional AI discourse. The first figure indicates that education's current state is problematic and that AI-driven education can cure this. In detail, the problem comprises of a variety of "gaps" that current education systems are deemed failing to close. For instance, education faces an "achievement gap" (Luckin et al., undated: 42) between richer and poorer students, which is assumed to mesh with a "socio-economic gap" (ibid). The second figure refers to the interconnection of lifelong learning (LL) and AI. In one text, it is stated that "[f]or many, education stops when they leave school or university. This is undesirable if we are to keep ahead of the machines." (Walsh 2017: 12). In two other texts, educational AI's supposed capability to enable "personalised, flexible, inclusive and engaging" (Luckin et al.: 11) learning is believed to enhance education in general (cp. ibid) and lifelong learning (cp. NSTC 2016: 10) in specific.

Both examples frame AI-driven education as obliged to and capable of the treatment of societal challenges. The first figure presents the pedagogic possibilities that AI systems inhere as to have the kind of power that is needed to attain socioeconomically equal distributions of academic achievement. With this, the student's educational experience is limited to the mere situation of mediation, and other factors crucial to educational success are excluded, such as a student's social background (cp. Bourdieu/Passeron 1971). However, the argumentative figure of attributing wide-ranging effectiveness is not unique to the phenomenon of educational AI; as Klebl elucidates, the use of technology for educational purposes has a reputation for effecting micro- and macro-level changes within education systems, a claim not easily substantiated though (cp. 2007: 3–4). Similar argumentations that recognize technology as the cure for problems in education, though not so much focused on inequality problems, can be located in the 1960s discourse on the so-called teaching machines, the predecessors of today's AI-driven learning technology. The second figure, besides from constructing rivalry between humans and *the machines* by alluding to a human-machine dualism and not mentioning economic and political actors', policies' and decisions' role in the implementation of AI into the working world, asserts the necessity of (AI-driven) lifelong learning (LL) to ensure the workforce's adaptation to AI-induced societal changes. The idea of the interminability of education was initially tied to ideals of humanist education (cp. Leitner 2010: 164). From the 1960s onwards, concerning the knowledge-based transformation of economic production, the idea has taken on a new connotation (cp. ibid: 147–152). European politics gave buoyancy to education as an economic factor, eventually establishing LL as an influential key concept (cp.

ibid: 152). From a viewpoint of educational governance, the notion of LL focuses on individual learning as a strategy of managing societal, economic and social change (cp. ibid: 164), holding the individual (as opposed to collective types of social entities) responsible for the adequacy of their learning efforts, and their educational self-management. In this perspective, the second figure refers to the replacement of the once and for all qualified alumnus by the self-managing lifelong learner whose needs are in turn promised to be serviced by educational AI's capacity for enhancing learning, that is making it even more flexible, personalised, inclusive and engaging.

A Reconstructive Approach to the Creation of Educational AI

From a viewpoint of socially, culturally, economically and politically informed and infused software production processes, the creation of educational AI can be described as a conglomeration involving intermediate practices and processes, including coding, design, computerizing ontological and educational certainties, funding and promotion, and implementing the application into existing educational or scientific practices and settings. According to Jörissen, who points out the crucial role design plays both in the configuration of things, digital or not, within the industrialised world (cp. 2015), the processes of designing educational AI systems can be assumed to encompass observations which feed the conceptualisation of relations between entities existing within everyday life (cp. ibid: 222–223). Consequently, designed things, and thus AI-driven educational technology, can be viewed as pervaded with knowledge about operant and desirable modi operandi within the portion of the world the application addresses and about desirable future application scenarios (cp. ibid). Such knowledge could both be tacit and explicit, *infusing the applications with normative concepts about pedagogy and sociality*, which could, for instance, cover the nature of AI's learning enabling capacities or mechanisms of learner motivation.

The further investigation of this issue draws on the circumstance that the design of AI-driven systems requires the formalisation of the knowledge to be implemented to being able to computerise it. Given the fact that to "advance personalized learning" (National Academy of Engineering, undated) is perceived as a grand engineering challenge today (cp. ibid), a general look at engineering-oriented perspectives on knowledge production seems fruitful. In AI engineering, the gathering of knowledge is usually referred to as knowledge engineering and the building of such formal structures (and sometimes the structure itself) as knowledge representation. The wording can too be located in promotional or application- and method-oriented texts concerning AI in education (cp. e.g., Katalnikowa et al. 2017). An online dictionary of computer science succinctly explains knowledge representation as "[t]he data-structure techniques and organizing notations that are used in artificial intelligence. These include semantic networks, frames, logic, production rules, and conceptual graphs." (Butterfield/

Ngondi 2016a), hyperlinking the techniques mentioned to other dictionary entries – except *the production rules* which, as a matter the dictionary has apparently nothing more to say about, appear greyed out. The dictionary's entry for knowledge representation is even shorter, denoting it as "[t]he branch of artificial intelligence that is concerned with building expert systems" (Butterfield/Ngondi 2016b). Definitions like these suggest that firstly, knowledge can be mirrored, that secondly, a system's knowledge structure is entirely fabricated by applying engineering-oriented rationales and engineering techniques, and that thirdly, the problem of knowledge gathering is limited to the effectuation of precast rules. The notions of knowledge engineering and knowledge representation, as they appear in this context, can thus be described as *selectively highlighting aspects of knowledge production and largely leaving out issues of productive knowledge*.

A further look at both science and technology studies and research in engineering indicates a mixed state of affairs. An earlier anthropological study on the construction of knowledge in AI research and development shows that the surveyed engineers think of knowledge production as "a matter of information transfer, not of the construction or translation of knowledge" (Forsythe 1993: 459). A more current enquiry from the related field of self-quantification devices development (concerning, e.g., fitness watches, food tracking apps, etc.) indicates that programmers and designers unwittingly draw on tacit knowledge about working principles of pedagogy and sociality (cp. Klinge 2018: 18–23). Newer engineering-oriented literature appears to acknowledge, at least to a certain extent, the complexity of knowledge production by addressing method(olog)ical questions, such as how to elicit tacit knowledge from customers (e.g., Ferrari et al. 2016). However, the more general issues how tacit knowledge translates into explicit knowledge, and how such processes can be rendered intersubjectively comprehensible remain littered with many blind spots. The reason for this might be that tacit knowledge refers to multitudinous topics, including body, gender, rituals or learning, packaging "translation" attempts with generalization problems. The non-linguistic and non-numeric character of tacit knowledge (cp. Kraus 2017: 18) poses an additional obstacle, adding to generalization problems questions of commensurability.

When it is taken into account that, from a science and technology studies perspective, scientific knowledge itself can be seen as the result of layered and intermingled ordering and inscription processes, which hardly correspond to formalised rules of knowledge production (cp. Latour/Woolgar 1986: 244–252), another layer of knowledge construction uncovers. Thus, since the practices in engineering that are concerned with knowledge production construct what domain experts once constructed they can be termed *practices of knowledge reconstruction*. Knowledge reconstruction attempts which particularly regard educational knowledge have to satisfy the challenges the specific structure or order of educational knowledge poses, in particular, the variety of forms of educational knowledge (cp. Thiel 2007: 157–160) and often the indetermination of their mutual relations. For instance, the wide-ranging notion of education, understood as subjecting a person, usually thought of as a child or an adolescent, to the educative efforts of an educator, is thought of as conceptually inhering a tension between educative intentions and goals (and the explicit knowledge thereof) on the one side, and the tacit knowledge involved in respective educational practices on the other (cp. Budde 2017: 802). In conclusion, the *variety of educational knowledge forms*, their often-indeterminate *mutual relations* and the sophistication of *wide-ranging theoretical concepts* challenge the reconstruction of educational knowledge in AI engineering contexts.

Blurs like this might be the reason why in applications of educational AI there is a preference towards theoretical concepts that are short-ranged, already operationalized or relatively easy to operationalize, including, e. g., motivation, learning styles or behaviour. The well-disposed reader will probably have noticed that these are not genuinely educational but psychological concepts (although the author willingly acknowledges that education has always drawn from other disciplines). Firstly, it is therefore debatable whether AI-driven learning technology is indeed addressing educational – or rather psychological issues of learning. Secondly and consequently, in the case of broad dissemination of AI in educational contexts, the enforcement of a current boom of specific theoretical concepts concerning learning and education is imaginable. For instance, and concerning intelligent tutoring systems, the notion of skills appears to be popular, adding to the overall popularity of the underlying concept of competence, which is expressive for standardisation and evaluation regimens in European education systems. To sum up, by enacting its infused social and pedagogical knowledge continually, broadly disseminated AI-driven educational technology might *influence the societal and scientific concepts which serve to discriminate, specify, evaluate and understand educational phenomena*.

Disclosure of Rationales as Making-Transparent, and Implications for Learning and Teaching

Another point to consider is the way in which productive aspects of the knowledge pervasion of educational AI are discursively addressed, and how therein the notion of educational AI is constructed. The example I want to present stems from a promotional piece of AI literature (cp. Luckin et al., undated: 25). Here, through anticipatory appeasement rhetoric, the text attempts to neutralise the known critique on granting opaque AI systems extensive decision-making powers, for instance by letting them grade students' works. The critics' suppositional deprecation of obscured decision criteria and an unclear informational basis of the decisions made by AI systems is rejected by the solution the promotional text provides itself, saying that modern systems "enable the rationale for each decision taken by the system to be made explicit and understandable by humans" (ibid).

At first sight, the venture appears laudable in its pursuit to render the systems' functional principles transparent to their users. A closer look reveals that the approach is limited in it its presentation of rationales as the sole detail worth debating. Following the social diagnosis of Han (2012), the discursive figure, in its disarmingly anticipatory public – thus transparent – display of possible critique and its demand for transparency concerning the subject matter, can be seen as expressive for the "transparency society" (ibid). Here, transparency "simply confirms and optimizes the existing. Therefore, the transparency society coincides with post-politics. Only the depoliticized spaces are truly transparent." (ibid: 16). In Luckin et al., a known critique is confirmed and the criticised matter – non-transparent decision-making AI systems – falls subject to optimization and depoliticization. Supported by technologically deterministic argumentation patterns typical for the promotional AI discourse in general (as opposed to, e. g., social constructivist lines of argumentation), such as the evocation of an inevitable "AI revolution" (Walsh 2017) which "will transform our political, social and economic systems" (ibid: 14) and which is assumed to require urgent adaptation measures (cp. ibid: 11–14), the outlined discursive figure *presents educational AI as an issue without alternative, and therefore as irrelevant to political debate and impervious to political and social action.*

Additionally, the analysis of production factors of AI-driven educational applications so far showed that such applications could hardly be viewed as entities that exclusively act by justifiable knowledge. From the viewpoint of layered and "messy" knowledge production, solutions like the one proposed by Luckin et al. require further processes of knowledge reconstruction as well as processes of mediating the reconstructed knowledge to the specific audience of educational professionals and learners. This renders AI-driven educational technology open to further infusions of knowledge. Thus, when, for instance, a university lecturer of a well-attended distance learning course suspects biased decision-making concerning the grades that were provided by an AI system, the disclosure of underlying rationales will only give partial insight into how the system has constituted the grades.

The demand for disclosure and the practices and techniques involved therein are productive themselves since they shape the very way of what it means to be an educator or subject to education. More transparency might evoke the attribution of more responsibility, both to professionals and learners. An example of disclosure methods in the field of educational AI is the concept of so-called open student models. They render particular aspects of the measured user activity visible to the student (and in some cases the teacher). To that end, like in University of Michigan's eCoach, "normative data visualizations" (University of Michigan, undated) are used. The underlying assumption is that being informed about one's learning activities by numbers, charts and diagrammes will foster motivation, adherence and thus performance, a behavioural science based approach widely spread in psychology and medicine. An additional increase in motivation and engagement is expected from the implementation of so-called open social student models. These use visualisation of the student's position within the crowd of learners. Such models establish possibilities for comparison and competition that exceed the informative value of plain overviews of grades by far. Whereas such methods might be insightful, and helping students, they might also be misleading on a larger scale, for instance when visualisations, supported by cultural conditioning, are mistaken for scientific evidence. Such misconception could, in turn, lead to the equally wrong perception that comparison and competition, undeniable features of learning due to mass education's selective function, are accessible in full through the narrowly focused comparison schemes of open (social) student models.

In this context, disclosure techniques such as open student models can be described as not merely producing transparency, in the promotional text arguably deemed a value in itself, but as a means for creating *action requiring transparency*. Such techniques can be named typical examples of "pedagogic measurement" (Manhart 2016: 57). Analysing organisational measurement practices, Manhart proposes that the ever-present acts of measuring social phenomena, which he describes to govern, stabilise and dynamise modern society, inhere a systemic aspiration to produce different results each time, and aim at the subject's adaptation (cp. Manhart 2016: 57–60). Manhart points out that

> [e]ach measurement does not only state what is but what one has hitherto learned and what one can, should and must learn in comparison to oneself and others. In the form of feedback, it directly permeates further processes of change, participating in their orientation, formation, and production. Feedback loops of the sort that measurement changes its subjects might be problematic concerning measurement theory, but functional concerning pedagogy in organisations. (2016: 59)

Disclosure techniques like University of Michigan's eCoach are productive at heart as they, in perpetually feeding back to the learners what they did and did not and in comparatively arranging and visualising that information, try to evoke and govern the self-managed student. One could say, the so-called chilling effect, referring to changed behaviours as a reaction to perceived surveillance, is precisely what open (social) student models pedagogically aim at, except that in this case observer and observed conjoin. Continuing this line of thought, open (social) student models can be reformulated as typically panoptic in the Foucauldian sense (cp. Foucault 2013: 251–291). It is the hallmark of panoptic disclosure techniques to not only prevent harm and wrongdoing but to improve the usefulness of those subjected to them: "the discipline as panoptic operation, as a functional relation which ought to enhance the exercise of power, that is to streamline it, facilitate it and make it more effective: a draft version of subtle coercive means for a future society" (ibid: 269). In this context, open (social) student models can be thought of as a way of normalising educational self-tracking as the basis for educational self-management, and, on a societal scale, as contributing to the socialisation of young citizens into ubiquitous transparency.

The role of educational professionals might as well be affected by demands for disclosed rationales. In a situation where a considerable part of the systems' production conditions remains obscure to public knowledge, educational professionals working jointly with AI systems might yet be urged to take ethical and educational responsibility. They might not only be able to demand the disclosure of rationales but be instructed or obliged to do so routinely. In this case, they would have to deal with issues like biased decision making in grading, admission, and tutoring or the effects of AI-enacted hidden curricula, resulting in the expansion of their responsibilities towards the supervision of hardly to predict actions performed by educational AI or the outsourcing of a considerable amount of pedagogical practice to computer scientists and thus non-experts on the subject of education. However, few (if any) of the productive effects can be supervised by the systems' end users alone, due to the obscure nature of the knowledge infused into and gathered by the educational AI.

Educational AI and Knowledge Production

The accumulation of knowledge through AI poses an overall notable aspect of the phenomenon. The entanglement of actors involved in the production of educational AI on the one side and knowledge production through educational AI on the other shows by the example of the German Research Center for Artificial Intelligence. It supposedly is one of the world's largest institutions engaging in AI research. Its educational AI projects concern, e.g., professional education in the "industry 4.0", physical education of children and adolescents, learning about extremist aspirations in social networks or municipal data organisation and learning. The centre is organized as a public-private partnership, opaquely mingling public, economic and political interests and doings. Its funders, shareholders, and clients include, amongst others, the European Union, the German Federal Ministry of Education and Research, the German Research Foundation, Google Germany GmbH, Volkswagen AG, the University of Kaiserslautern, the federal state of Rhineland-Palatinate and the Deutsche Sportjugend.

The point here is that AI-driven educational technology is not solely about creating knowledge infused entities to enable the knowledge acquisition of learners. It is also about generating data exploitable for *producing practically applicable knowledge about those who attempt to teach and learn* with the help of data-driven AI or digital learning resources in general. Following Schäffer's general approach to the datafication of everyday life, such kind of knowledge can be described as unidirectional, practically relevant, and implicit to the ones whose actions are "datafied" (cp. Schäffer 2017: 476). It is created through the manifold yet obscure possibilities of data re-contextualisation (cp. ibid). Fed by the previous example of the research centre, the actors from science, economy and politics to whom such knowledge is highly valuable (cp. ibid), can be assumed to be organised in large and ramified, and therefore difficult to untangle networks of non-profit, private and public organisations. In this light, and regarding the sensitive field of education, the examination of privacy, data security and hidden curriculum issues, and of questions how far educational data may be commercialised and what commercialisation really means when private-public partnerships provide the framework for the creation of data gathering educational technology, is a pivotal desideratum for further research.

AI systems' potential concerning educational knowledge production must be evaluated with respect to the ways in which AI can partake in research. On the one side, scientists can (possibly jointly with an AI entity) interpret data generated by a specific AI application, e.g. an intelligent tutoring system. Here, the insights producible are limited to the particular context. Hence, instead of opening one big "black box of learning", as the promotional text of Luckin et al. suggests in implicit analogy to the promise of AI opening the black box of the brain (undated: 18), AI-driven research of this type enables the opening of rather numerous tiny black boxes of specifically contextualised learning.

On the other side, there are indeed compelling possibilities arising from the combination of AI-driven pattern finding techniques with vast amounts of "mined" educational data. However, so-called big data techniques in the humanities are not the "agnostic" (Anderson 2008) scientific silver bullet some want to make of it. Even in the case of systems deemed capable of self-learning, the AI entity requires the input of preliminary assumptions. For example, systems operating the k-means clustering algorithm need to be provided with the number of clusters to be found. Such necessities are not as trivial as they might seem. Concerning k-means, the amount of pre-set clusters affects the granularity of the created typology and therefore how and which aspects of the research topic are constituted. In sum, the potential of AI-driven educational research should be reflected carefully, with regard to privacy, educational governance, data security and data commercialisation issues, and also regarding the problem of layered knowledge infusion, including extensive yet highly selective quantification processes, possibly imbalanced preferences towards concepts that can straightforwardly be operationalized and the researchers' (tacit) knowledge about how to "set up" AI systems for specific research questions.

Conclusion

The analysis has drawn from a perspective of knowledge infused and knowledge reconstructing design and engineering processes, from a perspective of productive political, scientific and engineering discourses, and from the viewpoint that economic, scientific and public actors mediate the production of educational AI. Since the production of AI is multi-layered and its productive effects are inextricably bound to each other, the findings should be looked at as analytical and limited by the exploratory nature of the investigation. Systematic empirical analysis, e. g., of policy networks or educational practices utilizing AI, still poses an open desideratum.

The investigation's findings suggest that the discursive production of educational AI relates to the interwoven assumptions that education in general and specifically lifelong learning are obliged and able to remedy large-scale societal challenges and that the application of AI-driven educational technology can leverage this potential of education. The underlying logic points at the figure of the self-managed and self-responsible lifelong learner, who is deemed in need of personalised, flexible, inclusive and engaging learning opportunities that AI-driven technology is assumed to be capable of providing. The discursive framing of educational AI thus emphasises governing aspects of education and educational technology, concerning society in general as well as the learning subject.

Furthermore, educationally applied AI systems can be reformulated as educational actors infused with tacit and explicit knowledge. The knowledge of such systems can be theorised as being assembled through multiple layers of knowledge construction and reconstruction. Contrastingly, in engineering-oriented and promotional discourses it is perceived and presented as a mirrored knowledge that in the form of rationales can be reflected back to the systems' users. Educational AI has the potential to govern practices of learning and teaching through demanding depoliticizing transparency, aiming at pedagogically meant chilling effects and requiring the management of disclosed rationales behind AI-driven decision making for educational purposes. It participates in knowledge gathering practices both in educational research and big data analysis jointly with scientific, public and economic actors, whereby the opaqueness and unilateralism of big educational data research challenge the particularly sensitive area of education.

Acknowledgements

The author thanks Denise Klinge for her much appreciated critical remarks on several draft versions of the article. The author translated on his own citations from works not written in English.

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