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ORIGINAL ARTICLES

Automating Learning Situations in EdTech: Techno-Commercial Logic of Assetisation

Morten Hansen[1] · **Janja Komljenovic**[2]

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Abstract

Critical scholarship has already shown how automation processes may be problematic, for example, by reproducing social inequalities instead of removing them or requiring intense labour from education institutions' staff instead of easing the workload. Despite these critiques, automated interventions in education are expanding fast and often with limited scrutiny of the technological and commercial specificities of such processes. We build on existing debates by asking: does automation of learning situations contribute to assetisation processes in EdTech, and if so, how? Drawing on document analysis and interviews with EdTech companies' employees, we argue that automated interventions make assetisation possible. We trace their techno-commercial logic by analysing how learning situations are made tangible by constructing digital objects, and how they are automated through specific computational interventions. We identify three assetisation processes: First, the alienation of digital objects from students and staff deepens the companies' control of digital services offering automated learning interventions. Second, engagement fetishism—i.e., treating engagement as both the goal and means of automated learning situations—valorises particular forms of automation. And finally, techno-deterministic beliefs drive investment and policy into identified forms of automation, making higher education and EdTech constituents act 'as if' the automation of learning is feasible.

Keyword Learning · Automation · Digital platform · Assetisation · Software architecture

✉ Morten Hansen
mh892@cam.ac.uk

Janja Komljenovic
j.komljenovic@lancaster.ac.uk

[1] The University of Cambridge, Cambridge, UK

[2] Lancaster University, Lancaster, UK

Introduction

Education technology (EdTech) companies are breathing new life into an old idea: education progress through automation (Watters 2021). EdTech companies are interested in portraying these processes as complex and bringing significant value to the learner and her educational institution, even when actual practices do not always reflect such imaginaries (Selwyn 2022). For example, EdTech companies may claim that artificial intelligence (AI) is a key part of their product, when in fact, actual computations are much simpler. It is therefore vital to disentangle EdTech companies' imagined and actual automation practices.

We propose the concept of 'automated learning situations' to disentangle automation imaginaries from actual practice. 'Learning situations' are the relationships between students, teachers, and learning artefacts in educational contexts. 'Automated' learning situations refer to automated interventions in one or more of these relationships. In practice, EdTech companies automate learning situations by capturing student actions on digital platforms, such as clicks, which they then use for computational intervention. For example, an EdTech platform may programmatically capture how a student engages with digital texts before computing various engagement scores or 'nudges' in order to affect her future behaviour.

It is useful to conceptualise such automation as techno-material relations mapped along two dimensions: digital objects and computing approaches. While current literature on EdTech platforms has already uncovered how platformisation reconfigures pedagogical autonomy, educational governance, infrastructural control, multisided markets, and much more (e.g. Kerssens and Van Dijck 2022; Napier and Orrick 2022; Nichols and Garcia 2022; Williamson et al. 2022), the two dimensions bring more conceptual clarity to the technological possibilities and limitations of actually existing automation practices. Furthermore, they allow us to unpack techno-commercial relationships between emergent automation and assetisation processes.

EdTech is embedded in the broader digital economy, which is increasingly rentier (Christophers 2020). This means that there is a move from creating value via production and selling commodities in the market, to extracting value through the control of access to assets (Mazzucato 2019). Assetisation is the process of turning things into assets (Muniesa et al. 2017). Depending on the situation, different things and processes can be assetised in different ways (Birch and Muniesa 2020). This includes taking products and services previously treated as commodities—something that can be owned through purchase and consequently fully controlled—and transforming them into something that can only be accessed through payment without change in ownership (Christophers 2020). A useful example is accessing textbooks in a digital form by paying a subscription to a provider such as Pearson+, instead of purchasing and owning physical book copies. Assetising a medium of delivery changes the implications for the user. For example, when customers buy a book, they own the material object but not the intellectual property (IP) rights. With the ownership of the book itself, i.e., the physical object, comes a measure of control: they can read the textbook as many times and whenever they want, write in the book, highlight passages, sell it to someone else, use it for some other purpose entirely, or even destroy it. On the contrary, paying a fee for accessing the electronic book via a platform transforms how users can engage with the content because the platform owner holds the control and follow-through rights (cf. Birch 2018): they decide when books are added and removed, what users can do with the book and for how long, and—crucially—what happens to associated user data. Generating revenue from a thing while maintaining ownership, control, and follow-through rights is an indication that this thing has been turned into an asset for its owner. We, therefore, ask: does the automation of learning situations contribute to assetisation processes in EdTech, and if so, how?

In what follows, we first present our conceptual and methodological approach. We then unpack the digital objects used to construct learning situations. Next, we discuss how interventions are automated differently depending on computing temporalities and complexities. We conclude by discussing three assetisation processes identified in the automation of learning situations: the alienation of digital objects from students and staff, the fetishisation of engagement, and techno-deterministic beliefs leading to acting 'as if' automation is feasible.

Our Approach

This paper is conceptual but empirically informed. We focus on business-to-business platforms targeting institutional customers like universities and enterprises. In other words, institutions pay a fee for students and staff to access and use the platforms.

We use the data collected as part of a larger research project on EdTech and assetisation through data practices. In this article, we use data from interviewing 20 professionals from 13 EdTech companies. The average age of these companies is 6 years. The interviews were conducted between October 2021 and May 2022. We asked respondents about their firm's business models, products, data practices, and strategies. Before each interview, we collected and analysed public documentation available for each company. We wrote an individual case analysis of each company and two overall finding reports, which were circulated and discussed with the research team. We complemented our insights with publicly available materials on other EdTech companies and practices, which were not part of our larger project but allowed us to exemplify some general dynamics uncovered through our research.

To contextualise assetisation processes, we theoretically drew from New Economic Sociology and Science and Technology Studies. This meant applying a processual lens on how firms and people that work in them transform objects and processes into assets (Birch and Muniesa 2020; Muniesa et al. 2017). We focus on the construction of digital objects and the computing approaches used to automate interventions, and consider if they could play a constitutive role in processes of software assetisation.

In the following, we discuss how such reconfiguration is partially contingent on the technological and legal limitations and opportunities inherent to digitalisation and computing more generally. We discuss part of our findings through ideal types.

Ideal types allow us to discuss our findings in ways that do not necessitate reference to identifiable companies or practices.

Constructing Learning Situations

Teaching and learning occur in learning situations. 'Learning situations' are relationships between students, teachers, and learning artefacts in educational contexts. 'Automated' learning situations bring automated interventions in one or more aspects of these relationships through algorithmic decisions or judgments materialised in outputs such as nudges, dashboards, groupings, and learning paths. To digitally automate learning situations, companies must construct the techno-material space needed for such operations. This is achieved by constructing up to three types of digital objects: the content object, the behaviour object, and the feedback object. Their analogue counterparts consist of learning content, student behaviour, and feedback from teachers and other sources. We now discuss these three digital objects to unpack the construction of the learning situation and what can be automated in it.

Digital Content Object

A content object is the component part of the curriculum being taught. The idea of content objects draws on a modular view of content where a body of knowledge can be divided into subcomponents. For example, mathematics can be divided into subcomponents such as algebra and geometry, which can be further subdivided into operations such as addition and subtraction. Content objects relate to content-specific learning objectives and can be thought of as rules and question-answers relations, which we elaborate on in the next section on digital behaviour objects. Most higher education (HE) platforms do not create nor own content. Instead, they tend to act as intermediaries between universities and learners (for example, online programme management platforms), individual teachers and learners (for example, Udemy), and publishers and universities (for example, digital book access platforms). In all these cases, content tends to be owned and controlled by universities, individual teachers, or publishers in the form of IP rights.

Without content ownership and IP rights, platforms are not free to break down and reorganise content, including its derivatives, such as automated text summaries or quizzes. If they wanted to use content objects in such automation processes, they would need to come to an agreement with publishers, which is time-consuming and costly. Consequently, EdTech companies construct other services on their platforms that do not violate IP rights. Common services include intelligence products, such as indicators and analytics of content usage. This is typically achieved by developing content-agnostic behavioural categories, such as tracking the pages students spend the most time reading. Another strategy is to capture content objects not subject to IP rights or where IP rights are sufficiently obfuscated, such as open-source content.

Digital Behaviour Object

The behaviour object is the smallest component of a student's behaviour that software can capture. Behaviour objects can be content-agnostic or content-specific. Behaviour objects are individual, relational, and temporal, which result from their aggregation, disaggregation, modelling, and comparison.

Online classroom participation data collected and analysed independently of content objects is an example of content-agnostic behaviour objects, such as mouse movements. Individual modelling would show statistics of an individual student's activity. The relational aspect would capture how a student's activity on a platform compares with others in a particular group, or which social groups are more or less active. Temporal modelling would compute the intensity of activities during specific periods. The key sources for content-agnostic behavioural data that we identified through our interviews were mouse movement, screen activity and inactivity, and reading patterns. We also found camera and microphone tracking activity in defined periods, but this was uncommon.

Content-specific behavioural objects are behaviour captured in such a way that they are assessable against learning outcomes. For example, a learning outcome could be the ability to repeat key learning points, write a text following particular stylistic requirements, or solve a mathematical or logical task. A content object can be matched to several content-specific behavioural objects, such as student responses to quizzes, mathematical problems, filling in blank statements, and playing games. Some of the companies we analysed also used optical character recognition and natural language processing to digitise written or spoken responses.

Over time, EdTech platforms typically build comprehensive anonymised accounts of each user, which allows for the computation of individual user generated data without breaking privacy legislation. Once user profiles are enriched with behaviour objects, they are aggregated, analysed, and turned into intelligence by the EdTech company. They are communicated back to individual students as personalisation. This can, for example, be applied in recommendation algorithms to identify snippets of information that might be useful to the student based on previous behaviour-feedback-content combinations. Another example is suggesting (sections of) books or articles based on what similar students have found helpful in similar situations. Personalisation computed through 'techniques of recursive divisibility (the drawing of lines of inclusive exclusion and exclusive inclusion)' (Lury and Day 2019: 31) therefore works as flows of data from groups of users to individual users, and back again. Personalisation through computation can thus be inherently relational, especially when the personalisation is content-agnostic, relying solely on behavioural objects for computing interventions.

Automated judgments from content-agnostic data tend to be diagnostic, for example, by spotting 'abnormal' behaviour (such as a prolonged absence from the platform or, on the contrary, intensive usage that might be indicatory of scraping activities) or identifying at 'risk students' by monitoring activity and inactivity. Content-specific behavioural objects, on the other hand, are used to make more direct claims about students' ability to demonstrate a learning outcome, multiple choice quizzes being a case in point.

Digital Feedback Object

The feedback object is the component part of the feedback that students receive in a learning situation. Sources of feedback objects include teachers, fellow students, and the software itself. We only found minimal computation on teacher feedback in our study, but there is a burgeoning debate on whether teacher functions could and should be automated through software (Selwyn 2019). Our participants reported that automating feedback for structured content, such as equations, grammar, or language learning, is easier than automating feedback for open assignments, such as essays. Automating evaluative statements about students' subtle distinctions in meaning making is particularly challenging because human language, evaluation, creativity, and cultural expression do not always follow law-like patterns.

A key idea in the EdTech industry is that software can capture and automate teacher feedback. A useful example is a flow chart (Fig. 1) produced by Graide—a UK EdTech company specialising in automated grading in STEM (science, technology, engineering, and mathematics). The appropriate feedback object can be produced and/or identified through one of three paths: (i) fully manual feedback by a human teacher in situations where the behaviour object cannot be recognised or where no centrally stored feedback object is available; (ii) partially manual feedback by a human teacher in situations where parts of the behaviour object can be matched with a feedback object; or (iii) fully automatic feedback by the machine where the behaviour object can be recognised as a repetition of a previous event for which the software already stores appropriate feedback. The logic here is that a continuously emerging self-augmenting system can be built around content, behaviour, and feedback objects.

At first glance, the figure seems to describe the techno-material flows Graide claims to structure through its platform. Previously encountered behaviour-content-feedback combinations become patterns from the techno-material space of past student–teacher interactions that are subsequently recognised and reproduced. New interactions are added to the ever-growing space, expanding the platform's technical capabilities. However, the figure is not necessarily a neutral or objective description of the platform. It is a visual object meant for public consumption to produce a set of cognitive framings and expectations about the future. Beckert (2016) calls this a cognitive technology. As a marketing device, the figure mobilises a belief in the platform's ability to produce

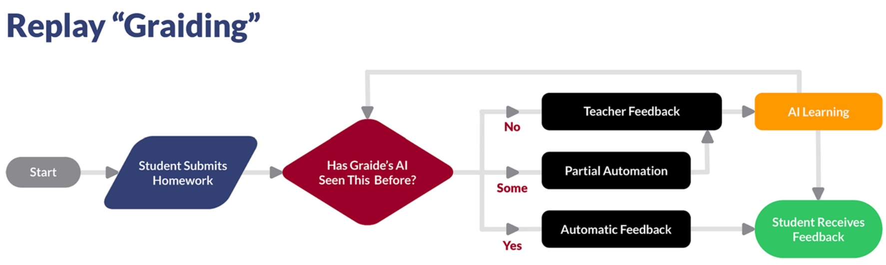

Fig. 1 Workflow from Graide. Source: Stanyon and Kainth (2021)

value for its users via network effects. It evokes the expectation that the software, over time, will become more efficient because the techno-material basis from which it can generate automated answers will grow. Finally, as a strategic plan, the figure outlines the technological future and roadmap that the company can strive towards: a future of automated assessment through the atomisation of feedback in STEM-related learning.

Teachers are integral to constructing the value of such feedback loops. Their input is turned into automated feedback capabilities, an asset the company controls. By capturing teachers' labour, the platform promises to generate use value and efficiency in the future. The cost of the subscription fee for accessing this asset is substantiated by the work that goes into building, maintaining, and growing the platform. However, the platform does not elaborate on the political-economic implications of such an asset construction.

Thus far, we have discussed how three types of digital objects can materialise learning situations. These objects are also used in producing automated interventions in learning situations, to which we turn next.

Automating Interventions

EdTech companies construct and frame automated interventions on their platforms. They can be organised on a matrix along two axes: computing architecture and temporality. Computing architecture of automated decision systems ranges from 'simple regression and decision tree models to complex deep learning models' (Richardson 2021: 19). The temporal dimension ranges from instantaneous to pre-emptive (cf. Witzenberger and Gulson 2021). Instantaneous decision processes allow for 'real-time' relational interventions. In contrast, pre-emptive decision processes only allow for discrete interventions based on computing decisions made in the past.

Instant and Pre-emptive Computing Temporalities

It can be argued that all digital computation is instant: if *y*, then *z* (Bucher 2018). For most EdTech interventions, however, this algorithmic judgment occurs before the student engages with the software, constituting a type of 'pre-emptive EdTech' (Witzenberger and Gulson 2021: 420). Thus, when we speak about 'instant' computation, we refer to computations that realise an infrastructure imaginary of real-time data tracking and intervention (Gulson and Witzenberger 2022; Williamson 2023). Therefore, instantaneity must have a relational quality that continuously moves between a totality of the environment and a centralised coordinating agent.

The EdTech companies we analysed run their platforms on cloud infrastructure, such as Amazon Web Services (AWS) or Microsoft's Azure. Consequently, their ability to process pre-emptive or instantaneous data analytics often depends on whether they pay for this computational service to cloud providers. Real-time data analytics is still an emergent area of business for large cloud infrastructure companies (AWS 2022) and is not the norm for EdTech platforms.

In EdTech, the more common approach is pre-emptive computing, where incoming data in the form of digital objects is processed in batches. For example, one of our interviewees explained that incoming user data was analysed and transferred onto a database during the evening. Any subsequent insights from analytics would then be ready for users the next morning. This means that a student who is reading a book on such a platform will see book recommendations based on data that was compiled the evening before.

By contrast, instantaneous computing computes the immediate discretisation[1] of learning situations into digital objects. Aggregation of these objects into a database makes immediate relational analysis and intervention possible. In other words, some degree of simplicity on both the observation and intervention side is necessary to achieve the efficiency needed for the computation processes to feel instantaneous. For example, if an EdTech platform is tracking a student while she is going through a learning problem, her behaviour must be sufficiently discretised so that the software can readily recognise if she needs an intervention. It must then be able to offer a relational solution to that problem by drawing on data that is being captured synchronously elsewhere on the platform.

Complex and Simple Computing Architecture

Complex computing architectures are those associated with artificial intelligence (AI). While leading definitions of AI generally refer to a machine's ability to think and act in rational and/or human ways (Russell and Norvig 2016), we concur with Gulson et al. that '[m]uch of the AI currently used in education is a variation of [more specific] machine learning' methods (2022: 8). The more complex computations we have observed include natural language processing applications, recommender systems, and pattern recognition. An example is a clustering algorithm that supports search or recommender systems: if a student is reading a book via a platform, books that are recommended as 'similar' have been identified through clustering algorithms that order the readings that students have previously enjoyed in 'similar' situations. The question is how intelligent these systems are.

The boundary between 'non-intelligent' and 'intelligent' software is unclear. Russell suggests a continuum from simple to complex software (Bruce-Lockhart 2022). Our interviewees reported that most of their computation approaches are simple and based on calculating averages, percentiles, or using decision trees to compute interventions such as sending an email 'nudge' or displaying analytics through a dashboard. Due to their prevalence, simple computations appear much more important than complex ones for understanding current and 'actually existing' EdTech practices (see also Selwyn 2022).

Such simple systems are rooted in behaviourist understandings of learning (Watters 2021). We found that in companies that claim to deliver automated and

[1] See Parisi (2016) for excellent discussion of the term 'discretization'.

personalised learning paths, many of the simple computations and feedback loops that they deployed echoed Skinner's belief that effective learning can be achieved through a set of pre-planned steps (1968: 47). If the student, for example, answers a digital quiz correctly on a learning platform, she will move on to the next question. If not, she will be given supportive material such as an explanatory video or a helpful passage in a book. While her learning path might be individualised in that instance, over time, the aim is to move her back onto an overarching learning trajectory.

We call this type of computing architecture 'simple', not because decision trees and systems cannot be elaborate but because such decisions work within a static and rule-bound regime. The goal is to get the student to display pre-defined, 'competent' behaviour that is encouraged through operant conditioning (Hock 2013; Watters 2021). While proponents of complex computing architecture promise to overcome this by using new AI approaches to construct a more generative set of automation processes between users and software, we did not find evidence of actual existing products that could currently deliver this.

The two dimensions of computing architecture and temporality are displayed in Fig. 2[2]. It outlines the potential technological capabilities that enable an EdTech platform to intervene in learning situations. The right-hand boxes present interventions that rely on instantaneous computing; the left-hand boxes include relational analytics relying on computing decisions made in the past. The top-hand boxes present interventions relying on complex computing; the bottom boxes include interventions relying on simple computing.

In the EdTech companies we analysed, the most common automation interventions were simple and pre-emptive. Our research also found practices of complex and pre-emptive interventions, as well as simple and instantaneous interventions. We did not find examples of complex and instantaneous interventions. Overall, the operational details and actual operational significance of complex computations were difficult to assess. Our findings suggest that some companies exaggerate the operational presence of complex computations in their promotional materials. This substantiates the need for further research into the nuts and bolts of automated interventions in EdTech, which are necessary to understand the political-economic consequences of automation. Furthermore, the automation of learning situations opens up the possibility for various assetisation moves, three of which we discuss next.

Assetising the Software

Automating learning situations refers to automating feedback loops between students and the totality of the technological artefacts delivered by an company. This is different from automating learning itself: students may participate in digital learning situations without actually learning anything, in the same way as

[2] Figure 2 presents a procedural typology of how interventions are structured. The matrix does not speak to whether such interventions are sound, appropriate, valuable, or meaningful. This will, among other, depend on how the EdTech company frames the learning situation it aims to automate

participation in traditional classrooms does not guarantee learning. As we have discussed, artefacts, such as quizzes, slides, nudges, and dashboards, are constituted by technological procedures that combine digital objects with computing techniques. Making the resulting learning situations controllable, meaningful, and valuable, and thereby part of a new asset relation, requires work. We unpack this work by focusing on the (a) alienation and detachment of the user from digital objects, (b) fetishisation of engagement, and (c) techno-deterministic beliefs promoting more automated imaginaries of education futures as realistic and thus something worthy of investment.

Alienation: Detaching Users and Digital Objects

The most common digital objects we observed were student behaviour objects, followed by content objects, and finally, feedback objects. This distribution is partly affected by the legal power of content creators in the HE sector. Commercial publishers hold onto their legal claim over digital content objects. They have the will and means to resist the detachment of content objects from their IP rights. Consequently, they are unlikely to lose control over products derived from this data, which can occur, for example, if other platforms develop quiz banks without giving the original publishers a commercial stake.

By contrast, students and staff do not hold the same concentration of legal power as publishers do; while their personal data is protected through data privacy regulation, users have little to no control over de-identified data or derivatives produced through aggregated user data. This lack of legal protection allows platforms to detach the use of platforms (i.e., learning and feedback behaviours) from the user (i.e., the student or the staff member) through the digitalisation of behavioural objects. These are then reassembled into digital products and services wholly controlled by the EdTech platform. For example, the well-known plagiarism software Turnitin compares student essays against a centralised text bank. Detachment occurs once an essay has been submitted, scanned, and incorporated into the centralised corpus against which future essays will be checked. Once uploaded to the platform, it becomes a constitutive component of the new asset, but the student has no control over it. The student cannot access it or see its inner operations, and they might even disagree with its existence altogether. Detachment and alienation are well understood in the literature on commodification and market-making (Callon 2021). However, detachment to create assets only holds a 'family resemblance' to detachment for commodification:

> [B]ecoming an asset is not the same as becoming a commodity. There is … family resemblance here. But the rule of entanglement and disentanglement, the calculative manipulations and the qualitative adjudications that characterise the object of the commercial transaction … are not the prime ingredients…. [Assets] must be neatly delineated … it must have the capacity to be owned or controlled … [and hold] economic value. The value it has is deter-

> mined by the possibility offered of converting it into money or of claiming revenues derived from it, sometime in the future. An asset ought to possess the properties that would enable it to be considered as a potential source of income for its proprietor—or, more broadly, of benefits for its controller. (Muniesa et al. 2017: 129-130)

Turnitin's commercial purpose for detachment—as was the case for all the companies we studied—is not to sell student data back to them. Instead, Turnitin's central value proposition is to track and coordinate the relation between students' essays and other texts. Detachment is essential because it allows Turnitin to entangle the student into valuable techno-material processes that she has no control over. Assetisation is possible precisely because customers find the software valuable, while the company controls it.

The production of such feedback objects is automated. Keeping the example of Turnitin, it is based on similarities and differences between a student's current behavioural object and a plurality of students' past behavioural objects that have been continuously saved and transformed into content objects on the cloud. Similarity scores are computed in a proprietary black-boxed algorithmic space; the students' behavioural objects, in part, constitute the space, but neither the student nor the teacher can access any subcomponents of the space. Computation happens in remote servers known as 'the cloud'. Users only receive computational outputs and snippets of this techno-material space in the form of feedback objects, which ensures that they cannot be reverse-engineered. Turnitin controls the platform, and universities pay a licence for access and for the service of receiving feedback objects. The service is valuable to HE institutions because it allows them to do something they could not do otherwise.

Fetishisation: Making Learning Situations Dependent on Content-Agnostic Automation

As discussed, EdTech companies can sidestep the technological and legal difficulties associated with IP rights if they build automated interventions through content-agnostic digital objects. However, the challenge is to frame learning situations so that resulting automated interventions seem meaningful and worth paying for to access. The most common strategy in tackling this challenge is by framing user engagement with the platform as a proxy for learning, such as learning analytics or dashboard visualisation, which has already been discussed extensively in the literature (Guzmán-Valenzuela et al. 2021). However, our respondents suggest that it is a struggle to frame such automation as being valuable, and that HE institutions are not willing to pay for dashboards. In short, it is unclear how useful they are in informing and improving learning.

Rather than backing away from seeing engagement as a proxy for learning, EdTech companies generally emphasise its relevance, leading to a kind of fetishism where engagement with the platform becomes both the purpose of learning situations and the input used to organise them. By doing this, they position ongoing content-agnostic feedback loops with their users as a core product feature. For example, the online teaching platform

Engagli focuses on live tracking and tailored intervention. The platform is constructed around the premise that the outcomes of a learning situation can be improved by using platform engagement data to intensify engagement with the platform. A company representative argues that one way of doing this is through live tracking and visualisation of student engagement, which is 'based on more than 70 points of data [per individual student] that the system is collecting in real time' (Wan 2020). Student behaviour is captured into calculable objects aggregated on the cloud to yield almost instantaneous feedback and produce a behavioural nudge to increase engagement with the platform. If institutions agree that such automated services are valuable, they must accept that they can only access them by paying a fee to the company.

Kerssens and van Dijck (2022) have noted that such computations have the potential to affect institutional and professional pedagogical autonomy. However, from an asset perspective, that is the point. The key asset move is to frame such computations as sufficiently valuable to education institutions and professionals so that it merits a fee. The material processes, places, and authorities of education judgment are physically moved away from the teacher towards software operating on the cloud. With that movement comes the shift in control and access that characterise processes of assetisation. The realm of this decision space is clearly demarcated and controlled: it starts and ends with the platform, and the only way to access it is through a subscription.

Techno-determinism: Acting 'As If' Automation Is Feasible

This asset move relates to constructing software as an asset to invest in, as judged through investment valuation and decision processes (Birch 2022). The process is structured by the discrepancy between the belief and the reality of automation sophistication and usefulness. A growing body of literature documents the hidden labour that goes into producing data for data-led approaches to education, and that goes into training AI systems more broadly (e.g. Bechmann and Bowker 2019; Selwyn 2021). However, planning and promoting systems as if these learning situations are feasible and valuable act as instruments of imagination in their own right, with causal powers on the social systems they seek to change (Beckert 2016). The value of actually existing technology thus stands in a constitutive relationship with speculations about technologies that may never materialise (Beckert 2016; Selwyn 2022; Williamson and Komljenovic 2022). For example, automatic interventions that rely on simple and pre-emptive computing that we discussed before (Fig. 2) may precisely be valued highly by investors because they are seen as a step towards more complex and instantaneous systems. In more cynical examples, simple computations may be marketed as more complex than they actually are, and without the ability to ever achieve this promise, in order to impress investors and customers.

Imagined automation processes take the properties of self-augmenting technical systems that, on the one hand, are striving towards a future that will become more automated while, on the other hand, implying that this future can never be fully automated. Indeed, if future learning is fully automated by unchanging software, the platform might be perceived as only enclosing existing public good (knowledge). The purpose and legitimacy of such an automation system would be hard to establish. After all, if the company's only role is to be a gatekeeper of static resources that can be copied at a

COMPUTING ARCHITECTURE		Pre-emptive	Instantaneous
	Complex	**Complex & pre-emptive automation intervention** *Process*: Batch processing of complex computing architecture *Prevalence:* uncommon Examples: relational dashboards updated overnight; categorisation of texts using machine learning.	**Complex & instantaneous automation intervention** *Process:* Real-time processing of complex computing architecture *Prevalence:* very rare *Examples*: live relational dashboards; live and relational computation for connecting students automatically.
	Simple	**Simple & pre-emptive automation intervention** *Process*: Batch processing of simple computing architecture *Prevalence:* very common *Examples:* identifying at risk students by indices; using decision trees to suggest predefined learning paths; sending nudge based on indices.	**Simple & instantaneous automation intervention** *Process:* Real-time processing of simple architecture *Prevalence:* uncommon *Examples*: live individualised dashboards; live nudging; live connecting students based on simple computations.
		COMPUTING TEMPORALITY	

Fig. 2 Automated intervention matrix

close-to-zero marginal cost, then this function could also be delivered as a commodity. The software's ability to constantly change as students and staff engage with it is therefore key to legitimising its asset state. By having something that is constantly being constructed, i.e. always more automated but never fully, the cognitive frame moves away from that of enclosing something already in existence and towards constructing something that will always be realised in the future. Our analysis suggests that EdTech entrepreneurs understand this dynamic and steer their tactics accordingly. This was particularly visible for some companies that rely on simple and pre-emptive computations but want to move into a more complex and instantaneous space.

Conclusion

EdTech platforms automate digital learning situations by constructing digital objects and computations. Key digital objects capture content, behaviour, and feedback. Computation approaches are divided into computing temporalities and architectures. The automation of learning situations contributes to the assetisation of educational software in conjunction with processes of detachment, fetishisation, and techno-determinism. These processes exemplify how edtech companies can assert control over their software while framing it as valuable. Such software assetisation processes have legal, pedagogical, and learner subjectivity implications.

Legally, IP held by actors other than the EdTech company itself, such as publishers or universities, complicated the construction of digital objects. For example, one company had decided not to generate automated quizzes from learning content owned by an external publisher because of the legal and commercial implications. Behavioural objects constructed using student and staff user data, on the other hand, were seen as less problematic to capture and use to develop subsequent products and services. This may be because these groups have not organised to make legal claims on revenue generated through their data. Legislative responses aimed at changing this state of affairs would need to go beyond current privacy regulation (Komljenovic 2021, 2022).

In terms of pedagogy, structuring EdTech products and services so intensely around behavioural objects and automated interventions affects commonly held meanings in established education practices. If student engagement is seen as a proxy for learning and clicks as a proxy for engagement, there is a risk that other notions of learning, such as situated learning (Lave and Wenger 1991), are put out of our attention. Under these conditions, learning could be obfuscated with behaviour objects, such as time spent on the platform. When behaviour objects under the disguise of learning or engagement become part of institutional policies and decisions, such as who gets rewarded or punished, it transforms the basis on which normative judgments are made about what constitutes a good education and who has the authority to make such claims.

Finally, while notions of improved efficiencies and reduction in human bias and error are key for legitimising the automation of learning situations (whether assetised or not), more research is needed to explore which types of activities we should and should not automate, and the wider social implication of automating learning situations by, for example, focusing on the dependencies built between the student and the platform through automation. The type of automation feedback that we noticed in our study is overwhelmingly focused on simple feedback loops in line with behaviourist traditions within which EdTech companies tend to work (Watters 2021). However, from the student's embedded point of view, those simple moments of automation make up an increasingly large part of the total learning situations that she accesses. It points to a world where things come to students automatically, in the form, for example, of recommendations or tips. Increased automation foreshadows an emerging intimacy between the machine and the human where, in effect, the platform becomes a type of extended cognition to the student, albeit—and as opposed to other traditional artefacts—in the form of a black-boxed asset controlled by the EdTech company. The better the platform knows the student through behavioural objects, the more entangled the extended cognition appears. Unless this box is pried open, student behaviour and platform calculation could end up in perpetual, asymmetric, and potentially self-legitimising feedback loops.

Asset perspectives thus bring counternarratives to dominant explanations of how cloud enabled platforms bring value to education. As we have shown in this article, processes of automation, platformisation, and cloudification are not simply about improving learning outcomes or systemic efficiencies. These processes are also used to alter existing control and use relations over software, which goes from being a tool located on hardware in the classroom that students and teachers do something with, to being an automated environment that operates on students and teachers from far away and black-boxed servers.

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Declarations

Conflict of Interest The authors declare no competing interests.

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References

AWS. (2022). 'Real-Time Data Streaming | Amazon Web Services.' Amazon Web Services, Inc. https://aws.amazon.com/streaming-data/real-time/. Accessed 9 October 2022.

Bechmann, A., & Bowker, G. C. (2019). Unsupervised by Any Other Name: Hidden Layers of Knowledge Production in Artificial Intelligence on Social Media. *Big Data & Society, 6*(1), 1–11. https://doi.org/10.1177/2053951718819569.

Beckert, J. (2016). *Imagined Futures: Fictional Expectations and Capitalist Dynamics*. Cambridge, MA: Harvard University Press.

Birch, K. (2018). What Is the Asset Condition? - F. Muniesa, L. Doganova, H. Ortiz, A. Pina-Stranger, F. Paterson, A. Bourgoin, V. Ehrenstein, P-A. Juven, D. Pontille, B. Saraç-Lesavre and G. Yon, Capitalization: A Cultural Guide (Paris, Presses des Mines, 2017). *Archives Européennes de Sociologie, 59*(3), 500–506. https://doi.org/10.1017/S000397561800036X.

Birch, K. (2022). Reflexive Expectations in Innovation Financing: An Analysis of Venture Capital as a Mode of Valuation. *Social Studies of Science*. https://doi.org/10.1177/03063127221118372.

Birch, K., & Muniesa, F. (Eds.). (2020). *Assetization: Turning Things into Assets in Technoscientific Capitalism*. Cambridge, MA: The MIT Press.

Bruce-Lockhart, A. (2022). What Is AI? Top Computer Scientist Stuart Russell Explains in This Video Interview. World Economic Forum, 14 June. https://www.weforum.org/agenda/2022/06/what-is-ai-stuart-russell-expert-explains-video/. Accessed 8 October 2022.

Bucher, T. (2018). *If...Then: Algorithmic Power and Politics*. New York: Oxford University Press.

Callon, M. (2021). *Markets in the Making: Rethinking Competition, Goods, and Innovation*. Brooklyn, NY: Zone Books.

Christophers, B. (2020). *Rentier Capitalism: Who Owns the Economy, and Who Pays for It?* London and New York: Verso.

Gulson, K. N., Sellar, S., & Webb, P. T. (2022). *Algorithms of Education How Datafication and Artificial Intelligence Shape Policy*. Minneapolis, MN and London, UK: University of Minnesota Press.

Gulson, K. N., & Witzenberger, K. (2022). Repackaging Authority: Artificial Intelligence, Automated Governance and Education Trade Shows. *Journal of Education Policy*, *37*(1), 145–160. https://doi.org/10.1080/02680939.2020.1785552.

Guzmán-Valenzuela, C., Gómez-González, C., Rojas-Murphy Tagle, A., & Lorca-Vyhmeister, A. (2021). Learning Analytics in Higher Education: A Preponderance of Analytics but Very Little Learning? *International Journal of Educational Technology in Higher Education, 18*(1), 23. https://doi.org/10.1186/2Fs41239-021-00258-x.

Hock, R. R. (2013). *Forty Studies That Changed Psychology: Explorations into the History of Psychological Research*. 7th Ed. Boston, MA and London, UK: Pearson.

Kerssens, N., & van Dijck, J. (2022). Governed by Edtech? Valuing Pedagogical Autonomy in a Platform Society. *Harvard Educational Review, 92*(2), 284–303. https://doi.org/10.17763/1943-5045-92.2.284.

Komljenovic, J. (2021). The Rise of Education Rentiers: Digital Platforms, Digital Data and Rents. *Learning, Media and Technology*, *46*(3), 320–332. https://doi.org/10.1080/17439884.2021.1891422.

Komljenovic, J. (2022). The Future of Value in Digitalised Higher Education: Why Data Privacy Should Not Be Our Biggest Concern. *Higher Education*, *83*, 119–135. https://doi.org/10.1007/s10734-020-00639-7.

Lave, J., & Wenger, E. (1991). *Situated Learning: Legitimate Peripheral Participation*. Cambridge: Cambridge University Press.

Lury, C., & Day, S. (2019). Algorithmic Personalization as a Mode of Individuation. *Theory, Culture & Society, 36*(2), 17–37. https://doi.org/10.1177/0263276418818888.

Mazzucato, M. (2019). *The Value of Everything: Making and Taking in the Global Economy*. London: Penguin.

Muniesa, F., Doganova, L., Ortiz, H., Pina-Stranger, A., Paterson, F., Bourgoin, A., Ehrenstein, V., Juven, P.-A., Pontille, D., Saraç-Lesavre, B., & Yon, G. (2017). *Capitalization: A Cultural Guide*. Paris: Presses des Mines.

Napier, A., & Orrick, A. (2022). The Economic, Social, and Political Dimensions of Platform Studies in Education. *Harvard Educational Review, 92*(2), 206–208. https://doi.org/10.17763/1943-5045-92.2.206.

Nichols, T. P., & Garcia, A. (2022). Platform Studies in Education. *Harvard Educational Review, 92*(2), 209–230. https://doi.org/10.17763/1943-5045-92.2.209.

Parisi, L. (2016). Automated Thinking and the Limits of Reason. *Cultural Studies ↔ Critical Methodologies, 16*(5), 471–481. https://doi.org/10.1177/1532708616655765.

Richardson, R. (2021). Defining and Demystifying Automated Decision Systems. https://papers.ssrn.com/abstract=3811708. Accessed 8 October 2022.

Russell, S., & Norvig, P. (2016). *Artificial Intelligence: A Modern Approach, Global Edition: A Modern Approach*. 3rd Ed. Harlow: Pearson Education.

Selwyn, N. (2019). *Should Robots Replace Teachers?: AI and the Future of Education*. Cambridge, UK: Polity Press.

Selwyn, N. (2021). The Human Labour of School Data: Exploring the Production of Digital Data in Schools. *Oxford Review of Education*, *47*(3), 353–368. https://doi.org/10.1080/03054985.2020.1835628.

Selwyn, N. (2022). The Future of AI and Education: Some Cautionary Notes. *European Journal of Education*, *57*(4), 620–631. https://doi.org/10.1111/ejed.12532.

Skinner, B. F. (1968). *The Technology of Teaching*. Englewood Cliffs, NJ: Prentice-Hall.

Stanyon, R., & Kainth, M. (2021). *Using Artificial Intelligence to Reduce Grading Workload and Increase Student Feedback*. 6 Bit Education, 15 November. https://www.graide.co.uk/blog/university-of-birmingham-research. Accessed 20 November 2022.

Wan, T. (2020). Coursera Couple Returns to Higher Ed With $14.5M to Recreate In-Person Learning, Online - EdSurge News. EdSurge, 14 October. https://www.edsurge.com/news/2020-10-14-coursera-couple-returns-to-higher-ed-with-14-5m-to-recreate-in-person-learning-online. Accessed 13 May 2022.

Watters, A. (2021). *Teaching Machines: The History of Personalized Learning*. Cambridge, MA: The MIT Press.

Williamson, B. (2023). Governing Through Infrastructural Control: Artificial Intelligence and Cloud Computing in the Data-Intensive State. In W. Housley, A. Edwards, R. Beneito-Montagut, & R. Fitzgerald (Eds.), *The SAGE Handbook of Digital Society*. Thousand Oaks, CA: SAGE.

Williamson, B., Gulson, K. N., Perrotta, C., & Witzenberger, K. (2022). Amazon and the New Global Connective Architectures of Education Governance. *Harvard Educational Review, 92*(2), 231–256. https://doi.org/10.17763/1943-5045-92.2.231.

Williamson, B., & Komljenovic, J. (2022). Investing in Imagined Digital Futures: The Techno-Financial 'Futuring' of Edtech Investors in Higher Education. *Critical Studies in Education*. https://doi.org/10.1080/17508487.2022.2081587.

Witzenberger, K., & Gulson, K. N. (2021). Why EdTech Is Always Right: Students, Data and Machines in Pre-Emptive Configurations. *Learning, Media and Technology*, *46*(4), 420–434. https://doi.org/10.1080/17439884.2021.1913181.

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