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ORIGINAL ARTICLES

Behind the Scenes of Co-designing AI and LA in K-12 Education

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Abstract

This article explores the complex challenges of co-designing an AI- and learning analytics (LA)-integrated learning management system (LMS). While co-design has been proposed as a human-centred design approach for scaling AI and LA adoption, our understanding of how these design processes play out in real-life settings remains limited. This study is based on ethnographic fieldwork in primary and secondary schools and employs a relational materialist approach to trace, visualise, and analyse the increasingly complex and transformative relations between a growing number of actors. The findings shed light on the intricate ecosystem in which AI and LA are being introduced and on the marketisation of K-12 education. Instead of following a rational and sequential approach that can be easily executed, the co-design process emerged as a series of events, shifting from solely generating ideas with teachers to integrating and commercialising the LMS into a school market with an already high prevalence of educational technology (EdTech). AI and LA in education, co-design and data-driven schooling served as negotiating ideas, *boundary objects*, which maintained connectivity between actors, despite limited AI and LA implementation and the development of a stand-alone app. Even though teachers and students were actively involved in the design decisions, the co-design process did not lead to extensive adoption of the LMS nor did it sufficiently address the ethical issues related to the unrestricted collection of student data.

Keywords Actor-network theory · AI in K-12 · Boundary objects · Co-design · Human-centred design · Learning analytics · Networks · Relationism

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Introduction

> (laughs) It's quite hard to keep up with the innovation process. I would have to follow you in the office. A lot is going on behind the scenes that you don't always see when you're at a school.
>
> Absolutely … To conclude, we needed to increase the use of the analytics parts of the platform. But as it collides with existing systems and is not fully developed, the tools were not tested as we wanted. That's why we created a stand-alone app because now it will be easier for them [teachers] to implement this tool and understand its effects and how we can further develop it. So, it was a way for us to advance the tools for data-driven education.

Conversation between the first author and the researcher/start-up founder.

The above excerpt sheds light on (1) the first author's struggle with understanding the process of co-designing an AI- and learning analytics (LA)-integrated K-12 learning management system (LMS) through merely observing in K-12 classrooms and (2) how the researcher/start-up founder, in response, points to the challenges involved with already-implemented systems that needed to be circumvented with an app to advance AI and LA in education. It also underscores the implicit nature of co-design processes, highlighting the necessity for greater attention to the underlying behind-the-scenes work.

This article aims to provide insights into the intricate complexities and challenges associated with co-designing digital technologies in education. More specifically, the article maps the power dynamics, tensions, and contradictions that arise among various social and material stakeholders, reflecting on the messiness, heterogeneity, and ever-evolving nature of the 'postdigital' (Jandrić et al. 2018; Macgilchrist 2021) in the design and use of an AI and LA integrated LMS.

The LMS was developed to facilitate lesson planning, management, and delivery of analytics through an LA dashboard, which reports on students' attendance, performance, motivation, enjoyment of lessons, and well-being. Drawing on fieldwork that was carried out over the course of two years, we use an *actor-network* metaphor (Latour 2007) to identify and untangle the relations between human and non-human actors involved in the different stages of the co-design process. Our focus on the actor-network formation(s) shares many similarities with human-centred aspirations of 'identifying the critical stakeholders, their relationships, and the contexts in which those systems will function' (Buckingham Shum and Luckin 2019: 1). However, a relational materialist lens foregrounds the materiality of such relationships and emphasises the socio-technical entanglements in which co-design, rather than 'solving' problems, enacts imagined educational futures (Macgilchrist et al. 2023). With all this in mind, the following questions frame our inquiries:

1. What are the relations between heterogeneous actors within the actor-network of the co-design project and how do they change over time?
2. What keeps actors connected at various stages of the actor-network formation(s)?

Advancing AI and LA in Education Through Co-design

The application of AI in educational contexts has been a subject of research for over 40 years, driven by the vision of enhancing and transforming established pedagogical and learning practices (Holmes and Tuomi 2022; Zawacki-Richter et al. 2019). The conducted research has developed along two complementary strands: (1) the creation of AI-based tools for classrooms (e.g. intelligent tutoring systems and virtual assistants) and (2) the establishment and use of analytical systems for the understanding, measurement, and improvement of learning (Holmes and Tuomi 2022). As AI research increasingly embraces a data-driven approach that leverages machine learning techniques for knowledge extraction, it often intersects with the domain of learning analytics (LA), which is a relatively new research area focusing on teaching and learning (Gašević et al. 2015; Buckingham Shum et al. 2019; Siemens 2013).

Today, AI and LA are already part of the 'global education industry' (Komljenovic and Lee Robertson 2017) and are increasingly being incorporated into education policy (Pedro et al. 2019; Tuomi 2018) and practice (Cone et al. 2022; Datnow and Hubbard 2016). With this follows the growing collection of digital student data through teaching aids, apps, and educational platforms used for e.g. automating grading, personalising instruction, and tracking student progress (Miao et al. 2021; Williamson 2019). Despite a surge in use over the past decade, the benefits of AI and LA in education are ambiguous and adoption uneven (Ferguson and Clow 2017; Viberg et al. 2018; Zawacki-Richter et al. 2019). In addition, the ethical implications of AI and LA in education related to students' privacy, algorithmic decision transparency and teachers' autonomy have come under increasing scrutiny (Berendt et al. 2020; Slade and Prinsloo 2017) and are reflected in a growing research focus on AI ethics (Borenstein et al. 2021; Cerratto Pargman and McGrath 2021).

Human-centred design (HCD) methods, such as co-design, have been proposed as a way to democratise the alignment of educational technologies with AI and LA (Buckingham Shum et al. 2019). The goal is to better meet the needs of teachers and students while also mitigating ethical concerns surrounding issues such as privacy, fairness, and transparency (Cukurova et al. 2019; Zytko et al. 2022). The empowerment of end users through active participation in the design process lies at the heart of HCD approaches, including *co-design* (Sanders and Stappers 2008) and *participatory design* (Bødker et al. 2022; Ehn and Kyng 1987). These approaches, often referred to interchangeably, are based on genuine participation. Participants actively push design ideas in concrete ways that matter to them and realise that many choices and alternatives co-exist (Bødker and Kyng 2018). While HCD methods are increasingly gaining attention in attempts to understand technology in educational practices (Pangrazio and Selwyn 2019; Tuhkala 2021), they still remain a novel approach in the development of AI and LA. In this context, HCD must be attuned to social dimensions, such as the expectations and values of teachers and students, while also recognising the material conditions of digitisation in schools throughout all stages of the design process (c.f. Giacomin 2014; Holstein and Aleven 2022). In addition, it has been suggested that HCD in LA should rely on educational theories to guide the design and implementation (Dimitriadis et al. 2021). However, AI and LA development also pose new challenges regarding what can and should be co-designed and in what way the generated design ideas should be implemented (Bratteteig and Verne 2018; Zytko et al. 2022). Other challenges relate to who should participate and what the full understanding of AI technologies entails (Bratteteig and Verne 2018). This includes participants' anticipation of the long-term effects of AI in education, which are crucial considerations in HCD (Lin and Van Brummelen 2021).

Although such considerations and challenges warrant further exploration, they embody co-design from an engineering perspective (Macgilchrist et al. 2023)—a primarily rational and sequential approach that can be suitably carried out, rather than an unfamiliar and unanimous process arising from situated and relational bounds (Crossley 2015; Gasson 2006). This paper presents a material-relational perspective on a design process that embraces the messiness and 'not-yet-known' aspects of reality (Richter et al. 2015). Here, co-design is perceived, on one hand, as an emergent and enacted process based on active participation (McKercher 2020) and, on the other hand, as a unifying idea, a *boundary object* (Star 1989) that strengthens relationships and facilitates collaboration among both human and non-human actors.

This study is situated within the Swedish educational landscape, increasingly characterised by marketisation (Baggesen Klitgaard 2007) and well-known for its substantial computer accessibility and adoption of EdTech as part of a political strategy (Rensfeldt and Player-Koro 2020). This accessibility is further enhanced by an all-encompassing platform infrastructure system that includes hardware, software, and administrative services (Hillman et al. 2020). Although AI integration is currently missing from Swedish educational policy, it has been recognised as a growing trend within the Swedish EdTech sector (Swedish Edtech Industry 2023).

In the remainder of the paper, we will present the premises that have helped us to operationalise our explorations in theory and practice. This includes outlining the various stages of producing and relationally analysing data. Findings are structured into three stages presenting the formations and transformations of the actor-network. Finally, we explore the implications of these findings within the context of educational futures, where AI and LA are deeply embedded.

Theoretical Premises

The present paper adopts a relational materialist perspective (Dépelteau 2013) and is aligned with the theoretical and methodological approaches attributed to *actor-network theory* (ANT) (Latour 1987; Law and Callon 1992). Rather than seeing human beings as isolated agents, relational materialism adopts the principle of *general symmetry* (Callon 1984) to examine the messy relationships between human and non-human entities (things, people, and ideas), in order to bring new understanding to social phenomena (Crossley 2015). Latour (2007: 76) describes this epistemological standpoint as 'to be symmetric, for us, simply means not to impose a priori some spurious asymmetry among human intentional action and a material world of causal relations'. Hence, a relational materialist approach enables us to shift in focus from the isolated examination of humans and technology to the exploration of socio-technical relations (see Jandrić et al. 2018). Such relations are constantly circulating like a 'space of fluids' turning things like power or agency into something that is enacted rather than fixed territories that can be studied at micro- or macro-levels (Latour 1999). More specifically, we apply a relational materialist approach to (1) methodologically follow heterogeneous entities, actors within the reported co-design project and analytically trace how they relate, and (2) to discern what sustains these relations. The concepts actor-network (Latour 1999) and boundary objects (Star and Griesemer 1989), presented in further detail below, have been central to these explorations.

Actor-Network

ANT represents science and technology as the creation of associations, *networks*, between human and non-human entities, *actors*. Actors are defined by their actions and are continuously transformed by, as well as transforming of, other actors. A productive way to think of an actor-network is as a rhizomatic web of interactions with no beginning or end (Fenwick and Edwards 2010). Notably, a network is not a thing out there, but a description of particular 'point-to-point connections' left behind by actors that can be traced and (re)assembled by the researcher (Latour 2007: 131).

Transferred to this study, the development of an LMS with AI and LA can be understood as an actor-network sustained by the relations between humans (e.g. teachers, students, developers, researchers), artefacts (e.g. venture capital, LMS, computers), and ideas (e.g. data-driven schooling, well-being). The number of point-to-point connections between actors is essential as they render networks durable and make invisible or 'black box' their inner workings (Latour 1999). The phenomenon of blackboxing means that when a device or a software operates effectively, the focus is directed only towards its inputs and outputs, rather than its internal complexity. Paradoxically, this also suggests that the more technology is conceived as successful, the less transparent it becomes (Latour 1999: 304). At the same time, actor-networks are only durable as long as actors interact; otherwise, they dissolve (Callon 1984; Walsham 1997).

To understand and describe how heterogeneous actors come together in networks and explain the durability of connections, ANT scholars often use the concept of *translations* (Fenwick and Edwards 2010). Translations describe the transformative, changing ways in which individual actors relate and how certain actors impose their priorities onto other actors. Translations can make visible the relations of power between actors (Michael 2016) by mapping how certain actors act upon and control other actors (Callon 1984; Callon and Latour 1981) or how the actor-network is mobilised to perform knowledge in certain ways (Fenwick and Landri 2012). However, ANT generally does not assume that actors inherently possess power. Instead, the analysis focuses on tracing power relations as heterogeneous actors effectively mobilise other actors (both human and non-human) in lasting relationships (Michael

2016). To understand and analytically approach the durability of the gradually expanding actor-networks in this study, we turned to the boundary object model (Star and Griesemer 1989) as it allowed us to examine translation processes from multiple viewpoints and not only from one single actor.

Boundary Objects

The boundary object model explains how collaboration between different actors from different social worlds can maintain the uniqueness of each community of practice (Lave and Wenger 1991). A boundary object can be an artefact or technique but also an inanimate thing, such as an idea, process, or concept, as long it allows for multiple interpretations. Thus, it is characterised by being simultaneously concrete and abstract, specific, and general. Residing between different social worlds and viewpoints, boundary objects are tailored to fit local purposes in ways often invisible to other actors. As put by Star and Griesemer (1989: 393), 'they are plastic enough to adapt to local needs and the constraints of the several parties employing them, yet robust enough to maintain a common identity across sites'. The boundary object model does not presuppose that one viewpoint is better than another; rather, it allows us to approach the entire actor-network. Methodologically, the relational material lens with the foregrounded concepts actor-network and boundary objects advocates for the ethnographic following of actors with a focus on the description and analysis of their relations (Latour 2007; Law 2004).

Methodology

The methodological focus has been to *follow actors* and *trace the actor-network* that constituted the co-design process. The fieldwork extended over 2 years, starting with initial interactions with participants in December 2020 and concluding with follow-up classroom observations in December 2022 (Fig. 1).

Following the Actors and Tracing the Network

The choice of the EdTech company was guided by a comprehensive review of educational technologies with AI that were implemented in Swedish K-12 schools and beyond. However, we realised early on that classroom observations in foreign

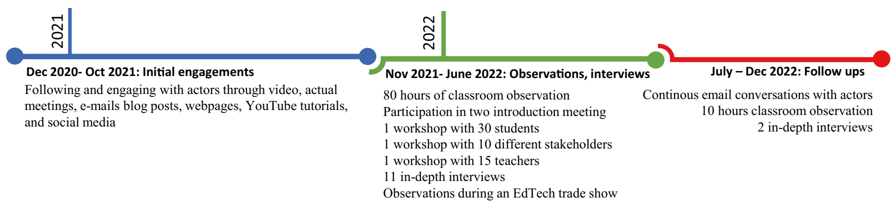

Fig. 1 Timeline of the following and tracing related to the co-design process

contexts could be challenging due to language barriers and unfamiliar curricula. Despite prevalent academic and commercial discourse, it was surprisingly difficult to locate an EdTech product in Sweden with AI functionalities targeting K-12. Moreover, not all companies are naturally inclined to reveal the workings of their systems or allow researchers to closely observe their operations. Consequently, our choice narrowed down to a company that had strong ties to research in both AI and LA and that was receptive to facilitating ethnographic work in schools. The EdTech company's LMS was at the time being tested and co-designed in collaboration with a couple of schools and teachers. Between December 2020 and October 2021, the tracing was conducted through blog posts, webpages, YouTube tutorials, and social media while also engaging with the start-up and the involved schools via email. This phase was extended due to fieldwork restrictions imposed by the Covid-19 pandemic. Intensified fieldwork was conducted in two schools between November 2021 and June 2022: one primary school with more than 1200 students aged 7–15 and one upper secondary school specialising in technology with approximately 450 students aged 16–19. Over the years, these schools had actively participated in numerous projects focusing on educational technologies. In this study, these schools were selected due to their extensive involvement in the co-design process of the LMS, with a dedicated group of seven teachers playing an active role in its implementation.

The fieldwork entailed over 80 h of observations conducted in six distinct classrooms, participation in two introductory meetings (each lasting 1 h), and attendance at three workshops (each spanning 2–3 h). These workshops involved various stakeholders, including upper secondary school students, teachers from multiple schools, a teaching aid publisher, and a group of 15 staff members from an upper secondary school. The observations were often followed by short conversations with teachers to confirm (or modify) what had been observed and further clarify teachers' and students' interactions with the LMS. Detailed field notes were taken from all observations, and a visit was made to a trade show where the start-up had a booth.

Based on what had been observed, 13 in-depth interviews were conducted between March and December 2022 with three teachers and one principal in the primary school, four teachers in the upper secondary school, one teacher in a lower secondary school, one representative from the local school authority, and three representatives from the EdTech company (UX designer, product developer, and founder, who also represents the university). The interviews spanned 50–90 min and aimed to broaden the understanding of the co-design process and the implementation of the LMS from multiple viewpoints. Nine of the interviews were audio-recorded, three video-recorded, and one was documented through notes on request of the respondent. During the autumn of 2022, the first author also followed up on the co-design process through emails with teachers and 10 h of observations in schools.

In compliance with the guidelines of the Swedish Research Council (Vetenskapsrådet 2017), informed consent was sent out between May and October 2022 to the participating schools (principals and teachers) where fieldwork was conducted. Additional consent was collected from students in those classrooms where observation took place and from all individual interviews. Confidentiality considerations prevent us from disclosing websites, company names, reports, or the names of individuals and their affiliations. However, it is important to clarify that no connections exist between any of the authors with the company that developed the LMS. Throughout the entire fieldwork, the first author operated as an independent researcher, with a focus on studying the introduction and implementation of AI and LA in teaching practices.

Producing the Actor-Network Accounts

The concepts of actor-networks and boundary objects have been put to work in tracing how actors relate and what effects emerge as a result. Guided by a 'method assemblage' approach (Law 2004), we have striven for an in-depth qualitative understanding of the transformations and actions taking place in a specific context while acknowledging our and the research method's active role in producing the actor-network realities (Ruming 2009). The interviews were listened to by the first author on several occasions, combined with repeated reading of interview transcriptions (verbatim), fieldnotes, relevant policy documents, blog posts, and other textual and visual information. As the analytical work unfolded, the attention shifted from what had been observed in schools to the scaling relations between heterogeneous actors. Evidence of these relationships was drawn from the authors' interpretation of the entire corpus of produced data, where the interviews provided insights about relations that could not be directly observed (Mazzei 2013).

The visual presentations of the actor-network were crafted by hand and analytically inspired by qualitative visual network analysis (VNA). VNA conceives networks as tools to *present*, rather than represent, the relational composition of heterogeneous actors (Venturini et al. 2015; Decuypere 2020). In contrast to VNA, which seeks to generate narratives out of the visual properties of the networks, the visual presentations in this study primarily seek to support the textual accounts of the relational bounds (c.f. Decuypere and Simons 2016; Law and Callon 1992). Therefore, software packages like Gephi, Cytoscape, and SocNetV, commonly applied to represent relational data collected in a pre-coded manner (Decuypere 2020), were not used.

Findings in Three Stages

The findings emphasise the changing relations and advancements of the co-design project in the actor-network formation and what keeps actors connected at three identified stages. Each visual presentation (Figs. 2, 3, and 4) highlights the actors referred to in the text during each stage by making other actors less visible (in grey). Actors have been presented in their organisational affiliation/roles relative to the co-design project and colour-coded to accentuate the heterogeneity of the network: research (blue), business (red), the start-up (purple), public governance (green), school entities (turquoise), EdTech (pink), and miscellaneous (yellow). Interview excerpts are included to provide a more comprehensive understanding of the relationships and actions within the network and so that 'the actors have some room to express themselves' (Latour 2007: 142).

Stage I: Steps Prior to the Co-design Project

> Well, it was in 2019, I carried out a couple of studies on learning analytics in higher education and we built a tool that helped us to optimise the courses and identify students at risk. … I had experimented with machine learning, and based on my experiences of data-driven methods combined with having observed existing learning management systems in K-12 and the gap that they left behind, [that] inspired me to build something … I had identified that these platforms had not been developed in a user-centred way, that the users were not involved systematically … so here was an opportunity to do something differently. (Researcher/start-up founder)

The opportunity 'to do something differently' marks the starting point for a series of interactions between heterogenous actors, characterising the set-up of the co-design project and the actor-network formation (Fig. 2). In 2019, there exists an AI-based software that has been tried out in academic programs by a group of researchers with the aim to improve the learning outcomes and identify students at risk of dropout. There also exist ideas of developing a more user-centred LMS for schools, together with teachers and students.

First, the AI-based software (1) catches the attention of a representative at the university's holding company (2) that is seeking to speed up the commercialisation of research outputs. The holding company representative offers one of the researchers at the university (3) the opportunity to develop and commercialise the researcher's idea of an LMS that can support teachers through data collection in the classroom. Rather than collecting data on easy-to-capture student activity (Gašević et al. 2015), the idea is to develop a system that collects data during lessons and delivers actionable insights related to students' performance, motivation, enjoyment of lessons, and well-being. An accelerator specialising in EdTech (4) assists in the foundation of a start-up (5), which makes it possible to attract venture capital (6) and recruit a CEO, developers, and UX designers. The start-up establishes connections with a municipal

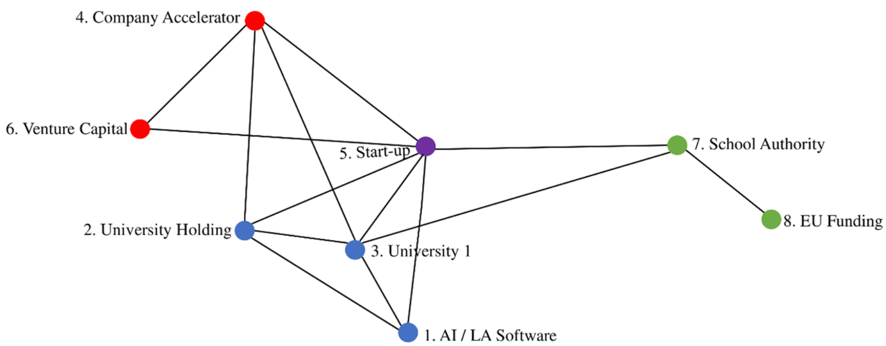

Fig. 2 The first steps of the actor-network formation, laying the ground for the co-design process

school authority (7) that is seeking EU funding to enhance the digital competencies in schools and investigate the potential of data-driven school improvement and educational technology more broadly (8).

The visual presentation of stage I (Fig. 2) shows how a triple-helix alliance (Etzkowitz 2008) between academia, educational governance, and business sets the scene for the realisation of the LMS prototype and the co-design process. In this process of translation, actors were bound to each other despite having different goals concerning the yet-to-be-developed LMS with AI. From the venture capitalist's viewpoint, the integration of AI into education was likely to be seen as a lucrative investment opportunity, while the local school authority was primarily concerned with enhancing and optimising educational processes. From a research perspective, AI, as well as LA, was a promising research area in the context of K-12 education. The promises of AI as well as LA in education (e.g. Luckin et al. 2016) were translated between actors within the network, making it possible for them to establish a mutual 'modus operandi' (Star and Griesemer 1989) sustaining the actor-network formation while enabling actors to reach different objectives. This idea suggests that student data processed with AI and LA algorithms can provide new and valuable insights to enhance teaching while also holding commercial potential. AI and LA in education served as a unifying factor, drawing various actors together and laying the groundwork for collaborations with teachers.

Stage II: Collaborating with Schools

In the spring of 2020, the SARS-CoV-2 virus (9) significantly impacts the debate surrounding EdTech innovation and adoption in schools (Cone et al. 2022; Williamson and Hogan 2020). The virus also helps to secure resources

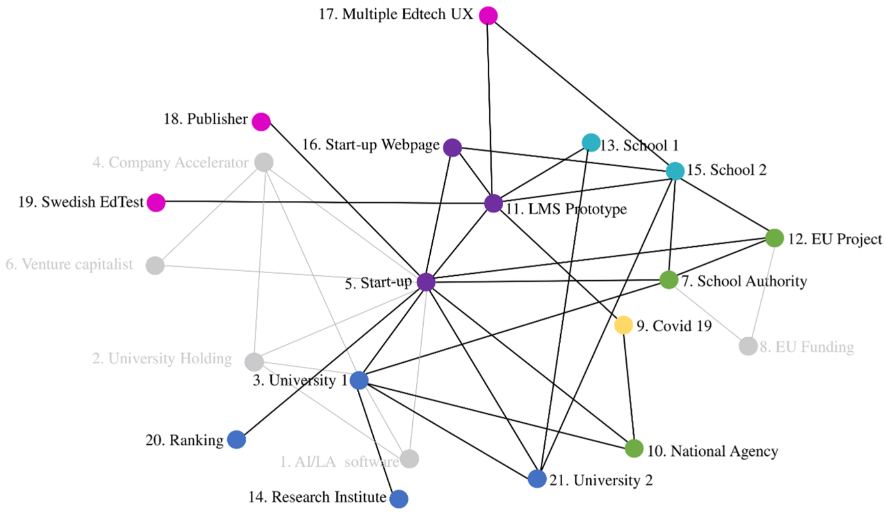

Fig. 3 More actors join the network, enabling the co-design process

for technology innovation through a National Agency (10). As illustrated in Fig. 3, the actor-network formation expands gradually, and the activities are centred around the co-design of the LMS prototype (11), where the assessment of students' well-being is an important feature. The focus on well-being data reflects a growing recognition in recent years among policymakers, researchers, and practitioners of the correlation between student well-being and academic achievement (European Commission 2021; Lindorff 2020).

The first version of the LMS prototype is tried out by teachers and students in a primary school (13). The school takes part in a professional development program organised by an independent research institute (14) in which the university (3) is involved. The LMS prototype is further iterated through monthly workshops centred around data-driven education as part of the EU project (12) initiated by the municipal school authority (7). In the end, one primary school (15), with a principal invested in advancing student well-being, is interested to try out the LMS prototype. The LMS prototype requires the selected group of teachers and their students, aged 6–15, to log in through the start-up webpage (16) and set up individual student accounts. Attendance is automatically logged, and the interface for both teachers and students is based around a calendar view. Teachers create a weekly schedule and insert lesson plans that can be monitored through a chat window, raised hands, and checklists. Data from students, including information from quizzes, entry and exit tickets from lessons, and daily performance and well-being self-assessments, are collated and visually represented as colourful lines and pie charts on a learning analytics dashboard, primarily intended for teacher use. Based on teachers' experiences and feedback, the LMS prototype changes.

> I wanted to try it out by myself, learning by doing, you know, and began using it [the LMS prototype] with all the students without knowing all the functions (…) and we had feedback for them and thoughts on how they could develop further and what we were missing and so on. (Teacher 1, School 2)

The developers and designers engage actively in the propositions of teachers and students by iteratively altering the functionalities of the LMS prototype. Gradually, the interface is simplified, and functionalities that teachers desire are added.

> That view, you won't see now, the students' view, it has completely changed after my and Sven's feedback, we wanted to make it as simple as possible. Before, there were buttons everywhere that you could press. It was less focused. I think the checklist is practically my idea because I suggested it so often and then it appeared (…) These bubbles were created after our feedback to show the learning objectives. How the exit tickets and screenings appear, the morning screening, and how to end a lesson. (Teacher 2, School 2)

Teachers' interests, here represented by the digital checklists and 'bubbles' with learning objectives, are translated and inscribed in the coding and design of the rapidly transforming LMS prototype. The design process also points back to teachers' broad familiarity with other apps and LMSs and their appreciation of the looks and features of other EdTech user interfaces (17).

> During those workshops, we are always asking about the tools that they're using today and what they like about them, and sometimes they show us how a quiz looks in another tool and how they check the answers, and what they see after. (UX designer)

Data collection, as part of a data-driven education, is a recurrent topic of discussion and negotiation between teachers, students, researchers, and developers. The involved teachers recognise the importance of monitoring student well-being and receiving feedback on their lessons. At the same time, teachers express concerns that very frequent monitoring can be distracting for students and hard to organise for teachers, which leads to a reduction of automatically generated surveys and data collection. They are also convinced that the analytical features are most effective when all teachers in a school collect data in a standardised way to identify trends. As achieving this level of standardisation may not be feasible in the near future, teachers tend to be less systematic in their approach. Contradictions also arise when teachers are asked to self-report their general well-being and satisfaction with their lessons.

> So, we also got [questions], well if I had eaten breakfast, if I had slept well, etc. For me, it was nothing awkward, but what happens with that data then, should the principal sit and analyse, well, Sven doesn't eat breakfast in the morning, perhaps I can do my job well anyway. (Teacher 1, School 2)

As one teacher recalls, some are uncomfortable with sharing information about themselves. The inscribed ideas of frequent data collection of teachers of the LMS are therefore not translated into teachers' practices. As a result, the daily screening stops, again altering the configurations of the LMS prototype. To further increase the adoption of the LMS prototype, the start-up establishes a relationship with a publisher (18) who is willing to integrate digital textbook content through the LMS prototype. This is believed to advance the use of learning analytics in relation to students' progression and assessment and integrate machine learning algorithms to personalise content. The new ally also motivates the schools to engage in the continuous co-design process. The national testbed for EdTech (19) makes the actor-network more durable by promoting the LMS prototype alongside other technologies to be tested for free during the pandemic. In addition, a ranking of the LMS prototype among the 100 most promising AI companies in Sweden (20) strengthens the company's credibility and the links to academia. It is at this stage when the first author, affiliated with a different university and conducting an ethnographic study on AI in education (21), becomes engaged in the network.

As reflected during the second stage, AI and LA in education served as a boundary object in the actor-network but was at the same time a subject of negotiated translations as the collection of data was being materialised in teaching practices. Thus, AI and LA served rather as a vision or 'imaginary' of the future of education (Hrastinski et al. 2019) and were subsequently subject to local tailoring in relation to what data should be collected, how often, and at what level, according to local needs and conditions. However, the negotiations also uncovered the fragility of the actor-network, where an intense data collection effort risked breaking the alliance that, at this stage, relied heavily on the active participation of schools. Considering the continued active involvement of teachers, co-design evolved beyond a mere design process. It served as a boundary object during this stage, enhancing relationships and fostering collaboration among diverse actors despite emerging contradictions. The school's willingness to provide input on the LMS prototype and subsequent modifications drove the actions of actors and held together the network. Rather than a rational, problem-oriented engineering approach, co-design was marked by flexibility in its interpretation and continual negotiation, as illustrated by the teachers' refusal to provide data on their own well-being.

Stage III: System Integration and Commercialisation

In the autumn of 2021, venture capital from a leading EdTech investor (22), owned by a major educational company (23), secures the co-design process as well as the future of the start-up (5). Programmers and staff directly involved with sales and marketing are hired, altering the focus of the start-up company (5). As the LMS prototype has been tailored to the preferences of a group of primary school teachers and aligned with the type of EdTech software they appreciate, efforts are now being made to make the product more 'universal'. One municipal upper secondary school (24) and a lower secondary school (25) join the co-design process, and the start-up (5) intensifies its monitoring through weekly digital meetings, frequent classroom visits, and various workshops involving students and stakeholders outside of the school. As the collaboration intensifies, obstacles are being identified in relation to already-implemented LMS systems, which teachers and students use extensively (26, 27, 28). Teachers see little value in having their students log into the 'new' LMS prototype just to be redirected to their old one, where all lesson planning and resources are available.

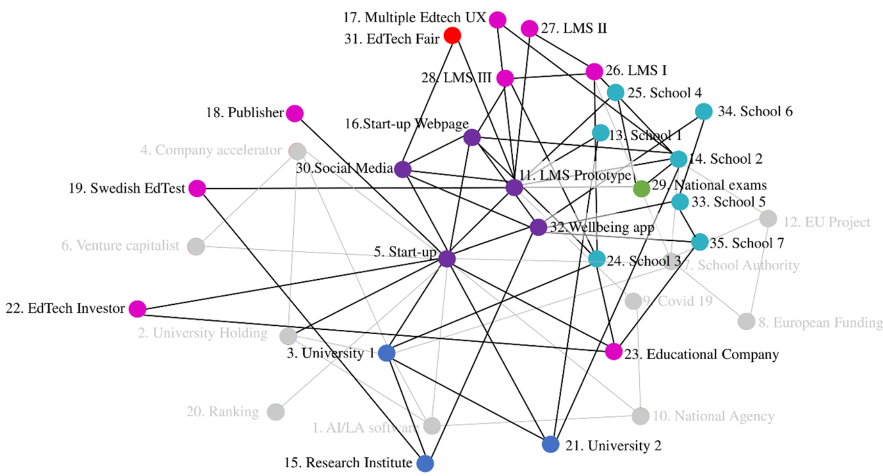

Fig. 4 Solidified by venture capital, the actor-network expands through the enrolment of additional schools and LMS systems

> Soon it dawned on me it didn't quite match, so my students logged in to the LMS prototype and then we didn't use it for anything other than doing this first check [morning screening] because I don't have a lot of material there but on the other LMS. (Teacher 1, School 3)

The 'double work' imposed by the LMS prototype, as expressed by the upper-secondary school teacher, outweighs the potential insights from data on teachers' self-reported well-being and results in low activity. This is taken seriously by the start-up. To stabilise the actor-network, competing LMSs need to be integrated. At the request of teachers and students, the co-design process now shifts focus from developing AI and LA functionality to integrating courses and other functions from the existing LMS system into the LMS prototype. Several co-design workshops are conducted at the upper secondary school to identify the features that students and teachers would like to see developed in the LMS prototype, considering their current use of the already-implemented LMS. Among the various generated design concepts, a dark mode display and a note-taking function are being realised. The participation of students in the co-design process strengthens the actor-network but does not address the challenges of data collection, which are critical for AI and LA development, or the time required for teachers to act based on the information presented through the learning analytics dashboard.

> Watching the analysis takes time. So, what does this analysis mean? We must have some initial discussion at some point and see, OK, so what is this and how can we interpret it? (Teacher 2, School 3)

As stated by one of the teachers, interpreting the graphical representations of the LA dashboard is not a simple translation process. Despite their involvement in the co-design process, teachers are pressed for time and have limited opportunities to discuss the visual feedback of the LA dashboard and to determine how they should respond to the aggregated analysis of students' responses. Furthermore, systemic factors such as national exams and other time-consuming assessments limit teachers' ability to adopt the LMS prototype (29). Again, the start-up, rather than risking that national exams could destabilise the network, acts by contracting one of the primary school teachers to develop 20 preparatory lessons targeting both teachers and parents who want to support their children in preparing for the exams. The network is strengthened by social media (30) and an EdTech trade show (31). Simultaneously, these activities heighten the company's financial responsibilities, pressing the need to secure additional venture capital for the development of their LMS. This in turn forces the start-up to focus on how to create a willingness to pay among schools. A professionalisation program on data-driven school improvement organised by the independent research and development institute (15) together with the university (3) attracts an independent upper secondary school (33) that is interested to monitor their students' well-being. The start-up company (5) engages the school to co-design a well-being app (32), which draws on the LMS prototype's morning screening. The stand-alone app is released in June 2022 on the start-up's website. Soon it is implemented in two additional schools (34, 35), one of which belongs to the education company (23). The actor-network is marked by the rapid expansion of relational boundaries with numerous K-12 schools, resulting in its transformation into a ‘black box’ (Latour 1999: 304), where the intricate interactions between diverse entities that construct and sustain it are hidden.

> Yes, well we have built several prototypes with AI functionality … we don't have the resources in the team to implement them (…) but in general, to apply machine learning, you need the right data of the right quality so what we have done these two–three years is to build infrastructure that enables AI innovation further down the line. (Researcher/start-up founder)

The researcher/start-up founder's account of the not yet implemented AI functionalities, due to inadequate data and resources, sheds light on the ongoing design of socio-technical futures in education (Hrastinski et al. 2019; Michael 2020; Rensfeldt and Player-Koro 2020). In these projected futures, AI and LA are considered to hold transformative potential. Yet their concrete embodiment in the practices of teachers may not always be apparent. It is also a telling example of the complex power dynamics involved in the introduction of AI and LA in an increasingly marketised and privatised school context.

As reflected in the third stage of the actor-network formation, the focus of the co-design shifted towards system integration and commercialisation, driven by renewed financial investments and already-implemented LMS. AI and LA in education as well as co-design remained important boundary objects to solidify the constantly transforming alliance. Nonetheless, these objects appeared to be increasingly challenged by local interpretation as the LMS prototype encountered obstacles: existing LMSs, national exams, and systemic constraints (including teachers' limited time). Since teachers did not adopt the LMS prototype to the extent necessary for AI and LA capabilities to become fully materialised in teacher practice, the co-design process evolved from collaborative activities, where teachers and students proactively offered design ideas (Bødker and Kyng 2018), to sharing feedback on the merits and shortcomings of implemented LMSs. Ultimately, this resulted in the incorporation of existing technological infrastructures, here understood as ‘historical materialities’ of the digital (Macgilchrist et al. 2023) into the LMS prototype. At the same time, the collaboration between diverse actors did not bring about significant changes to the ‘social world’ of each participant (Star and Griesemer 1989). Instead, as the actor-network expanded with the addition of new allies, such as venture capital and external research institutes, the focus shifted towards a broader embracement of *data-driven schooling* (c.f. Ikemoto and Marsh 2007; Selwyn 2022; Schildkamp et al. 2017). Data-driven schooling reflects the idea that digital data about students processed by AI and LA algorithms can offer insights to improve teaching and at the same time hold commercial value. This was particularly manifested by the launch of a commercially viable stand-alone well-being app. Data-driven schooling as the overarching idea helped to consolidate the actor-network and disregard the challenges of introducing and co-designing AI and LA in K-12 education. Hence, the idea of data-driven schooling as a boundary object, materialised through the app, stabilised the rapidly growing actor-network, which was becoming increasingly difficult to trace.

Concluding Discussion

This paper explores the messy unfolding of a co-design process by offering detailed insights into the complex interactions between software with AI and LA, a university holding company, research institutions, school authorities, a start-up, EU funding, K-12 schools, existing LMS systems, social media, venture capital, national exams, research institutes, national agencies, EdTech products, and numerous other heterogeneous actors. Each of these entities contributed to the various network configurations that brought the co-design process of AI- and LA-integrated LMS into being. This dynamic process continues to evolve and change course as new actors enter and existing ones depart from the actor-network.

We identified three boundary objects—AI and LA in education, co-design, and data-driven schooling—that brought actors together at different stages of actor-network formation and sustained the collaboration. These objects were subject to local interpretation and served as means to negotiate emerging challenges and contradictions related to e.g. teachers' scarce time and conviction to fully adopt LA functionalities, conflicts with previously implemented LMS, and the influence of commercial incentives in guiding profitable developments.

Notably, the presence of these boundary objects highlights certain narratives surrounding educational futures (Macgilchrist et al. 2023). The first object, AI and LA in education, posits that incorporating these technologies could significantly improve and transform teaching and learning—a potential highlighted by scholars like Luckin et al. (2016) and Siemens (2013). However, our findings suggest that the introduction of AI and LA in teaching practice is still a vague and unsettled phenomenon in the making that depends on significant adaptations from both teachers and developers (c.f. Sperling et al. 2022). Another common narrative suggests that involving teachers and students in co-design processes is a virtue in itself that will result in educational technologies that are aligned with teachers' needs and practices (Voorberg et al. 2015). This study demonstrates that even with teachers and students actively participating in the design process, the uptake of the LMS prototype was limited. Moreover, the co-design process did not result in significant attention to ethical concerns related to data collection. In this context, it is worth underlining that the teachers and students involved in the co-design had a high proficiency and interest in adopting EdTech, which is likely to have contributed to an engagement based on the narrative of AI and LA in education rather than the here-and-now concerns of e.g. what data should be collected and how they should be analysed and integrated in practice. Therefore, human-centred design approaches in AI and LA, where participants highly influence the design outcomes, can also prioritise pre-existing strategies, needs, and design, rather than addressing well-known ethical dilemmas. This also suggests that past technology design decisions continue to exert considerable influence on our 'postdigital' present and future. Data-driven schooling is the focus of yet another prevailing narrative. This narrative suggests that a vast majority of aspects related to educational practices can undergo 'datafication'—the transformation into quantifiable and computable data points—with the resultant data enabling teachers to provide more precise and evidence-based instruction (Selwyn

2022; Williamson 2019). Here, the teachers participating in the co-design process, while persuaded by such promising design futures, exhibited resistance towards extensive data gathering. Moreover, they encountered challenges in comprehending how to make use of the data presented in the LA dashboard.

In conclusion, while centred around a specific case study conducted in the Swedish educational context during the Covid-19 pandemic, this paper contributes to our understanding of the multitude of challenges linked to a human-centred design approach of designing educational futures with AI and LA. The study further elucidates the entanglement of educational practices in K-12 (in Sweden and beyond) with digital and platformed technologies and the marketisation of education at large (Cone et al. 2022; Rensfeldt and Player-Koro 2020). The increasing influence of the private sector and civil society organisations in the realm of education leads to an intricate give-and-take of services and competences, where several actors have multiple interests. It remains unclear whether everyone wins from this exchange and if some actors gain most of the benefits while others must provide most of the (unpaid) labour (see Day et al. 2022). At the same time, and to our surprise, a striking characteristic of the actor-network configuration was how it developed in a seemingly pragmatic and unplanned way, which can best be manifested in teachers' resistance to extensive data collection and the launch of a stand-alone app in parallel with the ongoing development of a comprehensive LMS. The fact that the implementation of AI and LA was not fully materialised and therefore difficult to observe in classrooms shows that the power dynamics between actors is never a settled affair with a predictable, determined outcome. Translations can fail, and networks are brittle and may dissolve. Therefore, bringing together various stakeholders still seems to be a viable approach in the development of AI and LA for education. However, further research is needed to address the complex relational, socio-technical bounds of such design processes. In particular, more attention should be paid to the ethical and legal considerations related to data collection from teachers and students, as these are growing significantly critical in the enactments of desirable educational futures.

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Declarations

Conflicts of Interest The authors declare no competing interests.

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