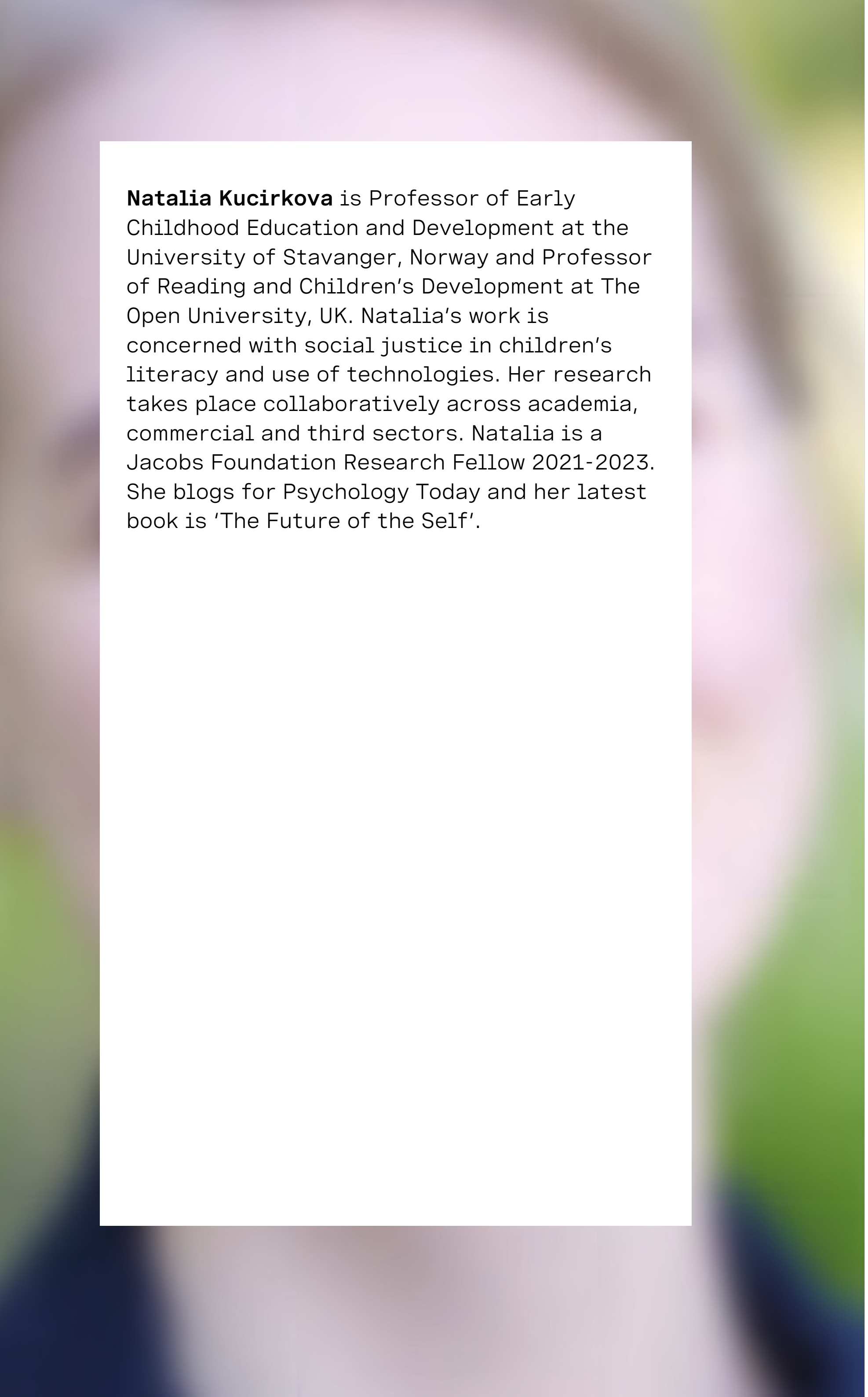

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The promise and pitfalls of personalised learning with new EdTech

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The coronavirus pandemic offered a unique opportunity to rethink the use of educational technologies (EdTech) for home and remote learning. EdTech brought the classroom home, facilitating teachers' access to communication with students and their families, collaboration among peers and management of digital information. While some EdTech platforms are designed to work offline, most of today's EdTech rely on online design solutions that process personal data. Some are designed with algorithms that can dynamically tailor the learning content according to individual students' progress and engagement. Such adaptive, data-driven EdTech is often described with the umbrella term 'digital personalised learning'. Although digital personalised learning design tends to motivate learners and streamline educators' work, personalised learning with EdTech is not without its pitfalls.

In this essay, I critically examine personalised EdTech's claimed benefits and limitations, before making some theorised, as well as tried and tested, suggestions for addressing its shortcomings. I focus on the commercially driven design logic of personalised EdTech, which must be discussed, understood and reconceptualised if EdTech is to offer learning benefits to all students.

The benefits of data-driven, adaptive EdTech

Personalised learning means adapting content to individual learners; that is, adjusting generic content to increase and make better an individual student's learning experience. The cost of such personalisation is high, however, and the possibility of outsourcing some of the personalisation of such labour to technologies helps to drive the recent interest in data-driven EdTech.

In EdTech, data are processed by algorithms designed to group similar characteristics together and categorise patterns of engagement. This is helpful for providing personalised feedback when teachers can't attend to each individual student, thus saving teaching time. When using the Duolingo app, for example, students receive automatic personalised feedback on their progress through the app, along with assignments that are tailored to them based on Duolingo's personalised learning engine.

The sophistication of individual algorithms varies. Some only collect test scores while others contain artificially intelligent tutors, with very different applications available across school subject areas. The purpose of data use in EdTech also varies widely. Some EdTech are used for monitoring school attendance (e.g., AppSheet), while others are used for monitoring learning progress (e.g., Naviance). Some EdTech have added features that allow users to exercise some control over their experience. These rely on data contributed by users themselves or on data extracted automatically by individual apps, games and platforms. With creative apps such as Scratch, for example, students can make their own designs, and with Night Zookeeper they can write their own stories.

Given the variety in how data are used and for what purpose, it is difficult to provide a simple account of the benefits and limitations of each EdTech application. What is crucial to consider when thinking about the added value of personalised EdTech is *how* the technology uses personal data and the algorithms processing that data.

The commercial design of EdTech

There is no doubt that data collection has provided a huge opportunity for the commercial sector. Commercial interest in data use is reflected in some features of EdTech that follow the logic relevant for economic but not learning gain. The commercial side of personalisation increases the benefits first and foremost for the commercial provider, and then for the user. The consequences of this have been widely reported in terms of data misuse, but the underlying design principles are less well known in the EdTech circles.

There are essentially two design principles that need to be understood here: (1) the principle of exponential data growth and the assumption that more data is always better; and (2) the like-like design principle and the assumption that recommending similar content is always beneficial. Both assumptions are rooted in economic theories about profit and psychological theories about engagement. These assumptions do not follow educational theories.

Commercial assumption 1: Exponential data growth

With data-collecting tools in almost everyone's pocket, the quantity and diverse nature of data increases every day. Experts predict that 463 exabytes of data will be circulated worldwide by 2025 (Seeds Scientific, 2021). Personalised EdTech will contribute to such exponential growth of data in the 21st century. The hunt for more and more data is driven by a commercial logic: the data economy runs with the mantra 'more data is better data'. This exponential growth in data is part of trickle-down economics where those who aggregate data profit from the data value much more than those who produce it.

In Kucirkova (2021), I describe the problem of exponential data quantity in relation to growing data complexity and its impact on children's development. With data that are being collected through multiple channels of several technologies, the portfolio of child's data becomes complex and relatively comprehensive. On the one hand, this helps with diagnostics: for example, when composing a child's reading profile, knowing how much, where and in which way (digital/analogue) the child reads, which genres and types of texts the child accessed etc., can provide a more accurate reading profile than can be afforded by data from a single e-book session.

On the other hand, the data amount and complexity creates issues with data ownership (e.g., who owns children's data when they transition from kindergarten to school and later to university?), interpretation (e.g., which criteria are used to holistically interpret data on a child's behaviour collected from school, social media and other sources?) and deployment (e.g., which subject areas or developmental goals are prioritised for applying intelligence from data?). Aggregated data require a certain level of data literacy, that is, digital and social competence for processing and interpreting numbers, trends and patterns. Children and their key caregivers, parents and educators are generally not equipped with this competence. Given the large and varied data sources, it is more manageable and convenient for schools to delegate the processing and interpretation of data to EdTech providers, which empowers them to not only collect and process data, but also to construe meanings about the data, and thus directly influence decisions about children's lives. The increasing complexity of large amounts of data and the exponential data growth may enable an unprecedented form of social control through the data it creates (Williamson, 2019).

In the hunt for more and more data, we need to ask – why do we need all this data? Personalised EdTech is being designed with the commercial goal of collecting increasing amounts of data rather than the nuanced understanding of which data are necessary for which purpose. Exponential and uncritical data collection leads to so-called 'datafied' childhoods and data-driven schools (see, for example, Lupton & Williamson, 2017), where data-driven, numeric and test-based evaluations of students' abilities carry greater weight than human assessment, gradually de-professionalising and eroding trust in caregivers' and teachers' judgements about children.

Commercial assumption 2:
The like-like recommendations

The design of a large proportion of personalised EdTech is modelled on the like-like logic of recommendation algorithms embedded in social media platforms – if you like X, the system recommends something similar (XX), and then again something similar (XXX), so that you gradually get something that is more precisely relevant to the initial interest category. The logic works well when you look for a group sharing your niche interest, for example. The logic works less well for creating new ideas and expanding viewpoints.

The like-like logic locks users into bubbles of like-minded individuals, which carries the risk of reinforcing group views. With a steady flow of similar information presented as 'recommended' and 'just for you', the algorithms stealthily increase the feelings of shared belonging and universal truths. Homogeneity of thinking and lack of diversity are the breeding grounds for the dangerous pattern of groupthink (when a group reaches a poor decision because of similarity in ideology and background of the group members) and parochial empathy (when one feels more empathy towards those who are of similar background). When children are grouped according to similar scores, needs or preferences, the cognitive and social benefits that come with exposure to or active engagement with diversity are minimised. It is therefore essential to discuss and be aware of these design limitations so that they are avoided in EdTech design.

A like-like design in personalised EdTech is a far cry from design principles based on learning sciences. Instead of supporting collaboration and shared sustained thinking, the design promotes behaviourist learning. In such a limited model of learning, students' achievement is reduced to narrowly defined objectives where rewards are given for small task completion to extrinsically motivate students to continue with the task. Students are given badges for successful task performance, despite studies showing the ineffectiveness of such reward mechanisms for students' intrinsic motivation (Kyewski & Krämer, 2018). Each click or tap triggers a response that pushes the child towards a desired goal – as if there was only one right answer for each question. The like-like design exposes children to content that follows a linear trajectory of incremental progress, with little room for serendipitous discoveries or learning through surprise. Possibly, such a design is suited for drill learning, but not for understanding complex concepts (see Meyer et al., 2021).

The limitations of commercial design do not need to diminish EdTech's contribution to children's learning. The learning sciences offer frameworks that educators can use to critically appraise the contribution of personalised EdTech to their classrooms. To address the exponential data growth problem, data needs to be used strategically and proportionally.

Educational assumption 1:
Strategic cut-offs for data generation

To personalise learning, data should be used to widen students' horizons and enrich their social relationships. It follows that we need to stop thinking about personalised EdTech as a panacea for post-pandemic education. Instead, developers, designers and educators need to consider *which* aspects of the educational pathway should be personalised. This needs to happen in a dynamic framework. Tetzlaff, Schmiedek and Brod (2020) developed a dynamic framework for thinking about such strategic data use. Their framework highlights intra-individual variability as a source of information for facilitating teachers' own judgement that could replace automatic loops and thus enhance the instruction support. The framework helps us see personalised EdTech in terms of its different impact on different students and different types of data for different students' needs.

Educational assumption 2:
Personalise and diversify

Acknowledging the commercial interest in the design of personalised Web 2.0, we can quickly see why the content needs to be relevant from the retailer's perspective: offering their client a recommendation for a new coat that is a complete mismatch from what they browsed and purchased recently is unlikely to result in a transaction. In the case of personalised EdTech, recommendations for content need to be based both on content units that are similar and also content units that are different from the students and their immediate surroundings (Munnich & Ranney, 2019).

Research shows that learning that 'sticks' is learning that is effortful (Brown et al., 2014). Concepts that are remembered over time are those that require deeper and longer engagement, which often runs counter to learners' preferences. While adapting content to match learners' needs might engage them it may lack the cognitive challenge required for processing the learning content.

Redesigning EdTech with educational principles

Successful education programmes need to personalise as well as diversify, and EdTech can be designed to accommodate both educational ideals. Diversification is achieved with purposefully designed content that is different from personalised content, a mechanism we refer to as 'personalised pluralisation' (Kucirkova & Littleton, 2017). The optimal model combines personalised information (relevant to an individual student) with content that is relevant to collectives (relevant to the classroom or peer cohort). It follows that personalised education not only needs to be implemented, but also co-designed, with families, teachers and communities. Such an assets-based perspective has been used in personalised trackers, success plans and navigators that show individual progress in relation to the progress of the community (e.g., individualised success plans can be transformational if they are both personalised and relationships-driven; see Sacks & Sedaca, 2021).

Redesigning EdTech with these principles implies not leaving it to commercial providers but to the communities of users. With courses and design opportunities offered by organisations like, for example, The Raspberry Pi Foundation, teachers and students can be technology co-producers.
In other words, the sweet spot of learning lies in an optimal balance between the automation provided by EdTech and the teachers' and learners' own choices. The essence of this optimal balance is a combination of learners' agency with teachers' pedagogy *and* the technologies' affordances.

The '5 A's' of agency

So far in the essay, I have advocated co-design at the level of communities, and the importance of social relationships in learning. In these efforts, we need to reflect on and incorporate individual agency.

Agency, an individual's volition to make their own choices, can be thought of in terms of the '5 A's': Autonomy, Attachment, Authenticity, Aesthetics and Authorship. These '5 A's' are the learning ingredients underpinning children's volitional choices. If they are present, EdTech can be considered to offer an educational foundation, but if they are absent, the commercial design principles, with their highly contestable assumptions, may become enshrined as strategic verities.

To elaborate, design that limits children's agency turns Authorship into consumption. Children's contributions are reduced to the providers' pre-designed templates, as with subscription programmes that furnish children with ready-made stories. In contrast, with design that invites children's agency, such as, for example, with open-ended story-making apps (e.g., Our Story), children can be the Authors of their own content. With EdTech that strips children of their Autonomy, children's agency is replaced with dependency. This happens, for example, with automated feedback loops that recommend the same content over and over. The feelings of Attachment to or ownership of a creative idea turn into dependency on a product. The Authenticity of children's own creations is reduced, and their Aesthetic sense is overpowered with adult design.

It is not just children who are stripped of their agency. With some of the bestselling digital libraries, teachers are positioned as curators and monitors of data rather than as co-readers and mentors (Kucirkova & Cremin, 2018). They are de-professionalised by having to rely on dashboards and templates that operate with a simplistic model of learning and make decisions on their behalf. Participatory design of EdTech could avoid these blind spots, but very few EdTech developers adapt a participatory research design approach. Products are presented to schools as ready-made tools, and teachers are positioned as consultants and testers of finalised designs. Disappointingly few EdTech designers think of children's involvement beyond the testing of prototypes that have been fully conceptualised and designed by adults. And despite the well-established tradition of participatory research design with children in human–computer interaction studies (e.g., Alison Druin's work on cooperative inquiry; Druin, 1999), children as co-designers of technologies are rarely involved in commercial EdTech production.

Learners can self-regulate, and learning practices that afford students agency over their learning facilitate self-regulation. This has been recently researched with the possibility of using personalised visualisations, which are external references to support learning (Molenaar et al., 2020). As learners set their own goals, evaluate their own progress and use personalised technology to visualise the process, they increase the accuracy of their performance with EdTech. This illustrates how the combination of technology-mediated and user-generated design, such as personalised visualisations, enhances self-regulation, which is known to be implicated in learning.

Conclusion

Whether data-driven personalised education lives up to its promise to educate is not yet known. However, as described in this essay, there are robust evaluation principles to guide the efforts. So that EdTech lives up to its promise of using personal data for advancing children's learning, the commercial design principles need to be replaced with educational design principles.

First, EdTech should be designed in ways that not only respect children's privacy and comply with child-inclusive policy but also minimise unnecessary data generation. Second, EdTech should be underpinned by algorithms that advance educational, ethical, moral and social goals by purposefully diversifying learning content. This is achievable as long as the personalised EdTech industry, pedagogy and policy abandon approaches inspired by commercial personalised technologies and adapt a culture of evidence and participatory co-design. EdTech developers, researchers and practitioners need to collaborate to ensure that data are used *strategically* to benefit individual *and* collective learning that advances human agency.

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