Datafication and algorithmization of education: How do parents and students evaluate the appropriateness of learning analytics?

Marijn Martens[1,2], Ralf De Wolf[1,2], Lieven De Marez[1,2]

The published paper is accessible through: https://doi.org/10.1007/s10639-023-12124-6

[1]*Dept. Communication sciences, Ghent University, Sint-Pietersnieuwstraat 41, Ghent 9000, Belgium*
[2]*imec-mict-UGent, Miriam Makebaplein 1, Ghent 9000, Belgium*

Corresponding author:
Marijn Martens
Address: Miriam Makebaplein 1, 9000 Gent, Belgium,
Phone nr: 0032497388848
Mail: marijn.martens@ugent.be

Conflict of Interest - None

Acknowledgements & disclosures:

The paper is not under consideration elsewhere.

This work was supported by the Fonds Wetenschappelijk Onderzoek (FWO) under Grant 11F6819N. The funding body was not involved in the study design, the collection, analysis and interpretation of data, the writing of the report or the decision to submit the article for publication.

Datafication and algorithmization of education: How do parents and students evaluate the appropriateness of learning analytics?

Abstract

Algorithmic systems such as Learning Analytics (LA) are driving the datafication and algorithmization of education. In this research, we focus on the appropriateness of LA systems from the perspective of parents and students in secondary education. Anchored in the Contextual integrity framework (Nissenbaum, 2004), we conducted two survey studies ($N_{students}$=277, $N_{parents}$=1013) to investigate the descriptive data on how they evaluate the appropriateness of the data flows in LA systems, and how both populations differ in their evaluations. The results show that the most-used student-centered LA are perceived less appropriate than the less-used teacher-centered LA by both students and parents. The usage of personal characteristics in LA is perceived as least appropriate, in contrast to coarser class characteristics. Sharing insights of LA with institutions that are part of the traditional educational context, such as the school, is seen as the most appropriate, and more appropriate than sharing it with learning platforms or third parties (e.g., Big Tech). Overall, we found that parents evaluated the different elements of the dataflows embedded in LA as less appropriate than students. In the discussion, we argue that educational institutions should include the evaluation of both parents and students to further manage expectations and construct shared norms and practices when implementing LA in education.

Keywords: Learning Analytics, Appropriateness, Contextual integrity, Survey, Students, Parents

Data statement: The datasets generated during and/or analysed during the current study are available from the corresponding author on request. The data are not publicly available due to them containing information that could compromise research participant privacy and consent.

1 Introduction

Algorithms are everywhere. They are also increasingly developed and deployed in an educational context with claims of improved efficiency and effectivity (Du et al., 2021). Consequently, more data is deliberately and automatically being collected under the pretext of improving education (Breiter, 2016). Educational algorithms systems span from kindergarten to university, and include systems such as educational apps, school monitoring, classroom management software, and digital assessments. These systems target not only students but also teachers and institutions (Decuypere, 2021). They are implemented inside and outside of the classroom, gathering data from all kinds of actors, and thereby further complicating the everyday practices and processes of schools (Jarke & Breiter, 2019; Pangrazio et al., 2022; Takayama & Lingard, 2019). One of the most visible and discussed systems in education is Learning Analytics (LA). LA collects data about learners and their learning context in order to improve learning, or as Clow (2013, p. 685) describes it: "[Learning analytics is] the measurement, collection, analysis and reporting of data about learners and their contexts, for purposes of understanding and optimising learning and the environments in which it occurs".

Arguably, COVID-19 accelerated data collection practices in education worldwide. Digital education formats emerged and were adopted at an unimaginable pace. Digital changes that would traditionally take years or even decades to implement were presented as "frontline emergency services" and quickly adopted (Williamson et al., 2020). Indeed, the pandemic has had a significant impact on teaching and learning (Babbar & Gupta, 2022). Nonetheless, even before the COVID-19 pandemic concerns about datafication and algorithmization were not uncommon. These include concerns about students being configured into a "monoculture of the mind" through of standardized tests (Shahjahan, 2011), the reconfiguration and downgrading of teachers into data professionals (Lewis & Holloway, 2019; Ratner et al., 2019), the increasing platformization of education (Pangrazio et al., 2022), and concerns about privacy (Prinsloo et al., 2022).

The perspectives of teachers, the educational system, and policy makers on the datafication and new flows of data in education have been the subject of increasing scholarly attention (Lewis & Hartong, 2021; Lewis & Holloway, 2019; Morgan & Ibrahim, 2020; Ratner et al., 2019), Jarke and Breiter (2019) have argued to be mindful of other stakeholders as well. In line with Ruiz-Calleja et al. (2019) we consider students and parents as two important yet underexplored stakeholders. Students are an important stakeholder to consider, as they are directly influenced by the outcomes of LA. Parents are often only indirectly impacted by LA, but they play an important role as they are the liaison between the school and the home (Schneider et al., 2022). In this study, we consider both perspectives to be important and, therefore, devote our attention to students and parents and their perspective on LA.

As LA systems are complex and multi-faceted, we argue that it is important to focus on different possible data flows. We follow the Contextual integrity framework as put forward by Nissenbaum (2004), which focuses on the appropriateness of specific data flows. This framework differentiates between different characteristics of the data flow to define it in a specific context (i.e., sender, information type, receiver etc.). In this study we use these characteristics to delineate specifically what elements of the dataflows in LA students and parents consider appropriate. We put forward the following research questions:

RQ1: How do students and parents evaluate and compare the appropriateness of different data flows in LA?

RQ2: How do students and parents differ in their evaluation of LA and the data flows in LA?

In what follows, we first elaborate further on the datafication and algorithmization in education and then further operationalize the Contextual integrity framework in the context of LA.

Theoretical background

1.1 Datafication and algorithmization in education

"Governing by numbers'– reducing complex processes to simple numerical indicators and rankings for purposes of management and control – has become a defining feature of our times." (Shore & Wright, 2015, p. 22). In the context of education, collecting data of pupils in schools to track their performance has always been common practice, even before the emergence of algorithms and processes of datafication (Krein & Schiefner-Rohs, 2021). However, in the past two decades, data-drive decision-making has become omnipresent in education as "it is no longer acceptable to simply use anecdotes, gut feelings or opinions as the basis for decisions [in education]" (Mandinach, 2012, p. 71). Selwyn and colleagues (2021) argue that two main evolutions have defined education on this front. First, the turn towards datafication and metrification of schooling, and second, the proliferation of digital technologies and algorithmic systems. Overall, the dominant rhetoric around these evolutions revolves around more flexibility, efficiency, and accuracy within the education system (Selwyn et al., 2021).

Lewis and Holloway (2019) warn against the use of data-driven technologies that simplify the complexities of social processes and their evaluation. Focusing too much on quantifiable effectivity configures the education system towards knowledge that is always measurable, which could skew evaluations favouring these measures (Morgan & Ibrahim, 2020). Indeed, the logics embedded in such tools are not neutral, but shape our education system and redefine what matters and how that should be evaluated (Lewis & Holloway, 2019). Jarke and Breiter (2019, p.5) argue that "the datafication of education does not only transform education but also our understanding of education, of what is understood as 'good education', associated objectives and good practices."

Overall, the shift towards datafication and the algorithmization of education brings along many different challenges. Rather than treating these technologies as an 'add-on' it seems to fundamentally impact how learning is done. Indeed, multiple data flows in multiple directions involving a plethora of actors arise and change because of these algorithmic systems within the educational context (Lewis & Hartong, 2021). Apart from teachers and institutions, students and parents should also be considered as being directly or indirectly impacted by the outcomes of these technology changes.

Students are clearly one of the main actors experiencing an impact of these changes, as it is their education that is influenced. Multiple scholars, however, argue how the voices of students are mostly absent (K. M. L. Jones et al., 2020; Roberts et al., 2016; Tsai et al., 2020; Whitelock-Wainwright et al., 2019). Parents similarly play an important role in education as they determine their children's secondary schools, act as a liaison between school and home, and are expected to provide input to schools (Schneider et al., 2022). Parents of underage students, moreover, are also the owners of the (educational) personal data of their children (Hoel & Chen, 2016). Despite playing this crucial role in the school system, the perspectives of parents have been largely underexposed.

In what follows, we further argue why it is important to look at this datafication and algorithmization, and more specifically LA through the eyes of students and parents.

1.2 Learning analytics through the eyes of students and parents

A previous literature review on the implementation of LA in secondary education showed that the main goals to implement LA are to predict students' dropout and students' learning outcomes (Sousa et al., 2021). Only a small fraction (11.9%) of the LA systems they investigated was implemented to support teachers' decisions and reflections or other goals. Another literature review similarly stressed that most attention within LA is put on predictive learning analytics compared to LA that would otherwise enhance learning. Moreover, a disproportional part of LA predictions are based on student related variables as predictors, rather than including also teacher and institutional characteristics (Sghir et al., 2022). Ruiz-Calleja and colleagues (2019) argue that in their case-studies students and parents are often seen as the mere producers of data and not given any active role. Nonetheless, as they experience the potential impact of LA, students and parents should at least be consulted.

When reflecting on the students' perspective towards LA, we found that there is a complex interplay of expectations and concerns. Viberg and colleagues (2022) found that students' ideal expectations for LA were significantly higher than their predicted expectations. Moreover, they found that some respondents, but not all, have privacy concerns. This shows the heterogeneity among students. Other scholars argue that students expect a lot from their education institutions in terms of the protection of their personal data, and expect their data to be used in an ethical manner (Slade et al., 2019). Ifenthaler (2016), moreover, found that students are rather conservative when sharing data. Students remained concerned about their privacy and their control over what data is collected, what the purpose is, and what implications learning analytics could have (Slade et al., 2019). Following 100 interviews with undergraduate students, Jones and colleagues (2020) found that students presented nuanced arguments on what data should be collected and with whom it should be shared. Meanwhile, they observed that "institutions rarely inform their students about [learning analytics] practices" (p.1044), and thus exclude them from the process. Ultimately, some students are only willing to supply personal information because they believe it to be a prerequisite for receiving (good) education (Tsai et al., 2020).

To the best of our knowledge, parents have not yet been investigated on their attitudes towards learning analytics being used in the educational context of their children. Meanwhile, they are proven to be an essential shackle in the education chain because of their role as liaison and data owner (see above) and are presented as one of the four main stakeholders in the educational context (Gaftandzhieva et al., 2021; Schneider et al., 2022). When looking at how parents evaluate technology in education, they most often have a positive perception and believe that technology helps their children in the learning process (Ramírez-Rueda et al., 2021; Tsairidis et al., 2020). Nonetheless, these evaluations are dependent on the specific case and context. During COVID-19 lockdowns, for example, parents often expressed negative beliefs and feelings towards online learning (Dong et al., 2020).

When scholarly research focusses on the evaluation of LA, they often focus on LA as a holistic system. How the specific elements embedded in different LA are evaluated is less explored. Following the suggestions of Tsai and colleagues (2020), we put forward the contextual integrity framework (Nissenbaum, 2004) to better understand students' and parents' evaluation of the appropriateness of different goals, data and actors involved in the dataflows embedded in LA to gain both a broader and more in-depth insight in how students and parents evaluate LA systems. In what follows we clarify our hypothesis while relying on the contextual integrity framework.

1.3 Contextual integrity framework to study the appropriateness of dataflows in education

Contextual integrity expresses a justificatory framework for addressing privacy concerns and privacy norms (Nicholas et al., 2019; Nissenbaum, 2004; Shilton & Martin, 2013; Winter &

Davidson, 2019) and has been implemented in the educational context (Birnhack & Perry-Hazan, 2020; K. M. L. Jones et al., 2020; Tsai et al., 2020). The framework uses five parameters to describe the flow of data to evaluate the appropriateness of a particular data flow, namely: the sender, recipient, subject, information type, and transmission principle (Nissenbaum, 2004).

When investigating the appropriateness of specific data flows in LA, there is a wide variety of possibilities within the parameters proposed in the contextual integrity framework. Apart from these five parameters, Nissenbaum (2019) also stresses the importance of goals as a defining factor of a specific context missing in the original approach of contextual integrity, "I had not placed sufficient emphasis on functions, purposes (goals, ends), and values around which contexts are oriented." (p.226). Indeed, it could be argued that goals should be considered as an overarching boundary condition of what could be considered appropriate and what not within a context.

Following the contextual integrity framework, this survey study investigates students' and parents' perspective on LA in education and differentiates in the goals, what data is used (=information type & data subject) and who has access to the insights of the LA system (=recipient of information). The sender of the information and the transmission principle remain stable in each LA system we discuss. The sender is the school, and the transmission principle is based on parents or guardians signing a school agreement.

1.4 Comparing appropriateness of different elements of the dataflows within LA (RQ1)

1.4.1 The appropriateness of goals within LA

Du and colleagues (2021) and Sghir and colleagues (2022) found in their systematic literature reviews that LA can be focused on predicting performance, providing support to teachers or learners, detecting behavioral patterns, and predicting dropout. Most of the goals of LA are angled towards students, while the broad conceptualization of LA includes the full learning context, and thus other actors (e.g. teachers, schools) as well (Clow, 2013). We differentiate between LA that is directed to students (=student analytics), teachers (=teacher analytics) and schools (=school analytics), to stress the differences between the different subjects of the data (Nissenbaum, 2004, 2019). For student analytics, we included a LA system predicting students' performance, for teacher analytics we included a LA system evaluating teacher performance, and for school analytics we included a LA system prioritizing the auditing of the school. We argue that there could be a difference between the appropriateness of these different types of LA as they differ in subject, following the argument within the contextual integrity framework. We propose the following hypotheses:

H1a: There is a significant difference in how students evaluate the appropriateness of student analytics, teacher analytics, and school analytics.

H1b: There is a significant difference in how parents evaluate the appropriateness of student analytics, teacher analytics, and school analytics.

To identify possible differences within student analytics, there could be made a distinction in terms of the granularity of the insights (K. Jones & Salo, 2018). Many current LA applications provide insights on the cohort level, rather than focussing on individuals (Prinsloo et al., 2022). Taylor and colleagues (2016) argue that a shift towards this aggregated level, accommodates most ethical challenges. The question remains if individuals consider cohort level knowledge to be more appropriate than knowledge about an individual in the educational context. Predicting the future performance of a class is much coarser, and thus less personal, than predicting the future performance of an individual. Moreover, the subject of the info changes from a personal level to a group level, possibly influencing the appropriateness of that goal (Nissenbaum, 2004). We hypothesize in H2a and H2b that group insights are evaluated more appropriate than personal insights by students and parents respectively.

H2a: Students evaluate personal performance predicting LA as less appropriate than class performance predicting LA.

H2b: Parents evaluate personal performance predicting LA as less appropriate than class performance predicting LA.

Student analytics can also differ in terms of how impactful the insight of the LA system is. The impact or possible harm of a decision-making system has had some scholarly attention in many other contexts. Research on digital contact tracing during COVID-19, for example, showed that the appropriateness of higher impact goals (e.g. limiting access) was significantly lower than lower impact goals (e.g. advising quarantine) (Martens et al., 2021). The same research found a difference for high-impact triage for hospitals versus low-impact triage for hospitals. Araujo and colleagues (2020), moreover, found that peoples' attitudes towards algorithmic systems significantly differed between a high-impact and low-impact use case in the context of media, health and justice. Similarly, in education it is argued that minimizing adverse impacts and harm are one of the main ethical issues with LA (Sclater, 2016). Multiple ethical principles or frameworks include elements such as minimizing risk or harm. Possible harm has similarly been suggested as a barrier to use LA (Fritz & Whitmer, 2019; Kitto & Knight, 2019). Dropout prediction could be interpreted as a high-risk and thus high-impact goal within student analytics. We argue that students and parents evaluate dropout prediction (=high-impact goal) less appropriate than predicting student' performance (=low-impact goal). We propose the following hypotheses:

H3a: Students evaluate high-impact student analytics (dropout prediction) as less appropriate than low-impact student analytics (performance prediction).

H3b: Parents evaluate high-impact student analytics (dropout prediction) as less appropriate than low-impact student analytics (performance prediction).

1.4.2 The appropriateness of the data subject and information type used in LA

When zooming in on the types of data, scholars argue that there should be drawn a line between data that is traditionally already captured in an educational context, like attendance or performance, on the one side (Selwyn et al., 2021), and other digitally enabled data like trace data or behaviour tracking on the other side (Williamson, 2017). However, only delineating between what has been done and what is enabled through technology, ignores the transformative power of the quantification and algorithmization in education (see above). Schools are now, presumably, able to infer much more insights from the same types of data than before (Krein & Schiefner-Rohs, 2021; Selwyn et al., 2021).

Most often learning analytics cover data of students (Gursoy et al., 2017; Sghir et al., 2022). However, also other data subjects like the aggregated class level, teachers, and schools produce data that could be used in learning analytics (Clow, 2013; Sghir et al., 2022). In this study, we differentiate between the data that is traditionally used in LA, like student scoring in school, and other background information on different aggregation levels. For the latter, we focus on the background information of an individual (individual characteristics), a class (characteristics of the class group), and a school (school characteristics).

The contextual integrity framework (Nissenbaum, 2004) suggests that the dataflow within a LA system using personal performance information could be evaluated differently from a system using personal characteristics as they differ in information type. As educational institutions have always been collecting and using data like the scoring and progress of their students, it could be argued that the usage of personal performance is an accepted practice (Krein & Schiefner-Rohs, 2021). We, therefore, argue that using performance data in LA will be evaluated as more appropriate than using personal characteristics as the latter is not directly related to the educational context and has not been used as frequently before. We propose the following hypotheses:

H4a: Students evaluate using personal performance in school as more appropriate than using personal characteristics for LA

H4b: Parents evaluate using personal performance in school as more appropriate than using personal characteristics for LA

When looking at the characteristics of students on different aggregation levels (individual, class & school), we expect there to be a difference in perceived appropriateness between them as they vary in terms of data subject and are increasingly less personal (Nissenbaum, 2004). The granularity of the data in terms of the data subject and the specificity of the data have already been emphasized in research in education (K. M. L. Jones et al., 2020). Moreover, aggregating data on a higher level could speak to the ethical issues proposed by Khalil & Ebner (2016) and Taylor and colleagues (2016) about de-identifying personal data or analysing data on a coarser level to accommodate for ethical challenges. We propose the following hypotheses:

> **H5a**: Students evaluate the usage of personal characteristics as less appropriate than the usage of class group characteristics.
>
> **H5b**: Parents evaluate the usage of personal characteristics as less appropriate than the usage of class group characteristics.
>
> **H6a**: Students evaluate the usage of class group characteristics as less appropriate than the usage of school characteristics.
>
> **H6b**: Parents evaluate the usage of class group characteristics as less appropriate than the usage of school characteristics.

1.4.3 Appropriateness of recipient of insights of LA

Nissenbaum (2004) argues that also the recipient of insights could define the appropriateness of data flows. When applying this to LA, this could be interpreted as to who the insights of LA are being communicated. Because of the quantification and algorithmization in education a lot of new actors are introduced in the educational context, possibly accessing these insights (Lewis & Holloway, 2019; Ratner et al., 2019). To test whether parents and students evaluate these actors differently, we included the school, the learning platform and third parties as relevant recipients to investigate. In line with our reasoning for the data used in LA, we argue that actors traditionally situated within the educational context (e.g., school) will be evaluated as more appropriate than those who are not (e.g., learning platform). Moreover, we argue that the closer the 'new' actors are to the educational context, the more appropriate they are to access the LA insights. We propose following hypotheses:

> **H7a**: Students consider it more appropriate for the school to access LA insights than the learning platform.
>
> **H7b**: Parents consider it more appropriate for the school to access LA insights than the learning platform.
>
> **H8a**: Students consider it more appropriate for the learning platform to access LA insights than a third party.
>
> **H8b**: Parents consider it more appropriate for the learning platform to access LA insights than a third party.

1.5 Comparing students' to parents' evaluation the dataflows in LA (RQ2)

Empirical studies comparing parents' to students' attitudes towards technological changes in the educational context showed significant differences between students and parents. Zhu and colleagues (2018), for example, found that students were in general more positive towards the implementation of tablets in education than parents. Parents feared the potential negative effects of tablet use more. Parents and students differ in terms of their characteristics that could have an influence on their evaluation of technology and in extension LA systems. Parents are arguably less technologically literate and innovative than their children who belong to the digital resident generation (Kong, 2018). Some scholars found personal innovativeness or the willingness to try new things to be a good predictor for their evaluation of technology systems in education (Amid & Bangi, 2021; Farooq et al., 2017). Moreover, the type of impact for students is different than for parents as LA is aimed at improving the educational context in which students receive their education. We argue that there will be significant differences between how parents and how students evaluate LA on the different data flows in the LA systems (RQ2). We propose the following hypotheses:

H9: There is a difference between parents and students in how they evaluate student analytics focused on personal performance (H9a), class performance (H9b), personal drop-out risks (H9c), teacher analytics (H9d), and school analytics (H9e)

H10: There is a difference between parents and students in how they evaluate LA using personal school performance data (H10a), personal characteristics (H10b), class group characteristics (H10c), and school characteristics (H10d)

H11: There is a difference between parents and students in how they evaluate that the insight of LA is accessibly by the school (H11a), the learning platform (H11b), and a third party (H11c).

2 Method

To answer the research questions, we conducted two online questionnaires, one targeting parents and another targeting students from the 5th, 6th, or 7th year in secondary education. Students were recruited through schools and social media, while the parents were recruited through a professional agency using quota sampling. A total of 1636 parents and 688 students started the survey. After a validation check, 1013 parents and 277 students were retained. No significant relation was found between the dropouts and the sociodemographic characteristics. The sample of the students was weighted with a weighing index of maximum 1.42, to be representative in terms of gender for Flanders. The sample of students had an overrepresentation of students going to general secondary education (73%). As the sample for students was not representative for education type, insights from the student data and comparisons between students and parents should be interpreted exploratory. Parents were weighted with a maximum weighing index of 1.72 to be representative in terms of gender and education for Flanders.

To measure the individuals' appropriateness towards LA with different goals, data, and actors we used single item 5-point Likert scales (ranging from completely inappropriate to completely appropriate) to minimize the questionnaire load. We consider these single item Likert scales as interval data as they are designed to have equal distance between each of the choices and the answering options are balanced around a neutral "not appropriate, nor inappropriate". Moreover, all questions concerning the appropriateness of the different elements are consistent in their answering options. Doing so we follow the suggestions and rationale of the often cited Carifio and Perlo (2008) and Bishop and Herron (2015).

We first asked our respondents to evaluate the appropriateness of different possible goals of LA (i.e., "how appropriate would you evaluate a system predicting the risk of you/your kid to drop-out of school"). As we interpreted the goal of LA as an overarching and boundary condition of appropriateness (see above), the rest of the questionnaire was personalized and altered to display only the LA systems they evaluated as appropriate (scoring "neutral" or higher) in each question. All students and parents thus got all the questions, but they were personalized based on their previous answers. We asked how appropriate they would evaluate the usage of different kinds of data for such LA-systems (i.e., "How appropriate would you evaluate it if [appropriate LA systems] would use your/your kids' scores on tests, exams and exercises?"). Afterwards we did the same for what actors would have access to the insights of the appropriate LA goals (i.e., "How appropriate would you evaluate it if [these appropriate LA systems] would be accessibly by your/your kids' school?"). An overview of all variables, their means and SD can be found in table 1, their operationalisation can be found in appendix A.

To test our proposed hypotheses for research question 1, we conducted paired sample t-tests to compare the different goals, data, and actors. We used Cohen d to evaluate the effect size of significant differences. We considered a Cohen d of .2, .5 and .8 to represent a small, medium, and large effect size respectively (Rice & Harris, 2005). To answer research question 2, we first conducted independent sample t-tests comparing students to parents, then we conducted hierarchical linear regressions to test whether the predictive value of being a parent or student (coded as a dummy variable) changed when including gender (coded as a dummy variable).

	Construct	**Parents**		**Students**	
	Appropriateness of…	**Mean**	**SD**	**Mean**	**SD**
Goals	Student analytics – personal performance	2.99	1.02	3.43	1.14
	Student analytics – class performance	3.31	.95	3.54	.94
	Student analytics – personal drop-out risk	2.94	1.07	3.33	1.16
	Teacher analytics	3.54	1.02	3.99	.97
	School analytics	3.36	1.04	3.24	1.09
Data	Personal school scoring	3.51	1.05	4.06	.91
	Personal characteristics	2.80	1.12	2.71	1.08
	Class group characteristics	3.50	1.03	3.91	.90
	School characteristics	3.54	1.04	3.94	1.02
Institutions	School	3.62	.97	4.07	.80
	Learning platform	3.26	1.07	3.18	1.11
	Third party	2.49	1.17	2.23	1.15

Table 1: Overview of all variables, means, SD

3 Results

3.1 RQ1: The difference in appropriateness between different elements of data flows in LA

3.1.1 Students' and parents' evaluation of the appropriateness of goals within LA

When comparing the students' perceived appropriateness of LA predicting an individuals' student score (=student analytics) ($M=3.43$, $SD= 1.14$) with prioritizing the auditing of the school (=school analytics) ($M=3.24$, $SD=1.09$), they were not reciprocally different ($t(276)=1.993$, $p=.047$). Evaluating the teachers' performance (=Teacher analytics) ($M=3.99$, $SD=.96$), however, was perceived significantly more appropriate than student analytics ($t(276)=7.034$, $p<.001$, $d=.42$) and school analytics ($t(276)=10.590$, $p<.001$, $d=.636$). The difference between student analytics and teacher analytics had a small to medium effect size, while the difference between class analytics and teacher analytics had a medium to high effect size, partially confirming H1a.

For parents, we found a significant difference between the appropriateness of all the types of LA. Student analytics ($M=2.99$, $SD=1.02$) was found least appropriate and significantly less appropriate than school analytics ($M=3.36$, $SD=1.04$) ($t(1012)=10.110$, $p<.001$, $d=.318$) with a small to medium effect size. School analytics was perceived significantly less appropriate than teacher analytics ($M=3.54$, $SD= 1.02$) ($t(1012)=5.442$, $p<.001$, $d=.202$) with a small effect size. Logically, also student analytics was perceived less appropriate than teacher analytics ($t(1012)=15.579$, $p<.001$, $d=.489$) with almost a medium effect size. These insights confirm H1b.

When comparing the students' perceived appropriateness of student analytics on different aggregation levels, we see that the appropriateness of LA systems who aim to predict a students' performance ($M=3.43$, $SD=1.14$) compared to LA systems aiming to predict class performance ($M=3.54$, $SD=.94$) did not significantly differ ($t(276)=2.045$, $p=.021$) providing no evidence to confirm H2a. For parents, however, student analytics on the aggregation level of the class ($M=3.31$, $SD=.94$) was perceived significantly more appropriate than student analytics on the individual level ($M=2.99$, $SD=1.00$) ($t(1012)=11.210$, $p<.001$, $d=.352$) with a small to medium effect size, confirming H2b.

In terms of the impact of student analytics, no significant difference was found for students' perceived appropriateness of predicting dropout ($M=3.33$, $SD=1.16$) compared to predicting a student's performance ($M=3.43$, $SD=1.14$) ($t(276)=1.423$, $p=.078$). Equally for parents, there was no significant difference between the appropriateness of predicting dropout of students ($M=2.94$, $SD=1.07$) or predicting their performance ($M=2.99$, $SD= 1.02$) ($t(1012)=2.176$, $p=.015$), confirming neither H3a nor H3b.

3.1.2 Students' and parents' evaluation of the appropriateness of data used in LA systems

Comparing the appropriateness of different kinds of data to feed the LA systems to perform the goals deemed appropriate, we found that the appropriateness to use personal characteristics ($M_{student}=2.71$, $SD_{student}=1.08$) ($M_{parent}=2.80$, $SD_{parent}=1.12$) was found significantly less appropriate than using personal school performance information ($M_{student}=4.06$, $SD_{student}=.91$) ($M_{parent}=3.51$, $SD_{parent}=1.05$) with a big effect size for students ($t(276)=17.868$, $p<.001$, $d=1.073$), and a medium to big effect size for parents ($t(1012)=19.183$, $p<.001$, $d=.603$). Confirming H4a and H4b respectively.

When zooming in on the aggregation level of personal information, we found that the appropriateness of using personal information on the individual level ($M_{student}=2.71$, $SD_{student}=1.08$) ($M_{parent}=2.80$, $SD_{parent}=1.12$) was significantly lower than the appropriateness of using personal information on a class group level ($M_{student}=3.91$, $SD_{student}=.90$) ($M_{parent}=3.50$, $SD_{parent}=1.03$) with a big effect size for students ($t(276)=17.778$, $p<.001$, $d=1.067$) and a medium to big effect size for parents ($t(1012)=19.949$, $p<.001$, $d=.694$). Confirming H5a and H5b respectively.

The same remains true for parents if we go an aggregation level higher and compare the appropriateness of using personal information on a class group level (M=3.50, SD=1.03) with the appropriateness of using personal information on a school level (M=3.54, SD=1.04). They evaluate the usage of personal information on a school level as significantly more appropriate than on a class level (t(1012)=4.338, p<.001, d=.136), however, with a very small effect size. Weakly confirming H6b. For students, the difference between the appropriateness of using personal information of a class (M=3.91, SD=.90) is not significantly different from using personal information of a school (M=3.94, SD=1.02) (t(276)=.429, p=.334), rejecting H6a.

3.1.3 Students' and parents' evaluation of the appropriateness of access to insights of LA systems

When looking at the appropriateness to share insights of LA systems deemed appropriate, we see a significant differences between the appropriateness between all institutions. For students, sharing the LA systems' insights with their school (M=4.07, SD=.80) was deemed most appropriate and significantly more appropriate than sharing the insights with a learning platform (M=3.18, SD=1.11) (t(276)=12.867, p<.001, d=.773) with a medium to high effect size. Sharing the LA insights with a learning platform (M=3.18, SD=1.11) was, however, still more appropriate than sharing it with a third party (M=2.23, SD=1.15) (t(276)=13.842, p<.001, d=.831) with a high effect size. Confirming H7a and H8a.

For parents, the same is true. They evaluate the appropriateness of sharing the LA systems' insights with the school (M=3.62, SD=.97) the highest and significantly higher than sharing the insights with a learning platform (M=3.26, SD=1.07) (t(1012)=10.036, p<.001, d=.315) with a small to medium effect size. Sharing the LA insights with a learning platform (M=3.26, SD=1.07) was, also for the parents, more appropriate than sharing it with a third party (M=2.49, SD=1.17) (t(1012)=22.108, p<.001, d=.694) with a medium to high effect size. Confirming H7b and H8b. An overview of all the hypotheses and outcomes for RQ1 can be found in table 2.

Hypothesis	Outcome Student (Hxa)	Outcome Parent (Hxb)
H1: There is a significant difference in how students/parents evaluate the appropriateness of student analytics, teacher analytics, and school analytics.	**V (partially)**	**V**
H2: Students/parents evaluate personal performance predicting LA as less appropriate than class performance predicting LA.	**X**	**V**
H3: Students/parents evaluate high-impact student analytics (dropout prediction) as less appropriate than low-impact student analytics (performance prediction).	**X**	**X**
H4: Students/parents evaluate using personal performance in school as more appropriate than using personal characteristics for LA.	**V**	**V**
H5: Students/parents evaluate the usage of personal characteristics as less appropriate than the usage of class group characteristics.	**V**	**V**
H6: Students/parents evaluate the usage of class group characteristics as less appropriate than the usage of school characteristics.	**X**	**V**
H7: Students/parents consider it more appropriate for the school to access LA insights than the learning platform.	**V**	**V**
H8: Students/parents consider it more appropriate for the learning platform to access LA insights than a third party.	**V**	**V**

Table 2: Overview of hypotheses and outcomes for RQ1

3.2 RQ2: The difference between parents and students in their analysis of the elements of data flows in LA

We see that for most elements making up the different dataflows in LA, student evaluate them significantly more appropriate than parents. This is true for all student analytics, including those focused on personal performance (H9a) (t(1287)=6.271, p<.001, M_{parent}=2.99, SD_{parent}=1.02,

$M_{student}$=3.43, $SD_{student}$=1.14), those focused on class performance (H9b) (t(1287)=3.627, $p<.001$, M_{parent}=3.31, SD_{parent}=.95, $M_{student}$=3.54, $SD_{student}$=.94), and those focused on personal drop-out risks (H9c) (t(1287)=5.341, $p<.001$, M_{parent}=2.94, SD_{parent}=1.07, $M_{student}$=3.33, $SD_{student}$=1.16). The same is true for teacher analytics (H9d) (t(1287)=6.580, $p<.001$, M_{parent}=3.54, SD_{parent}=1.02, $M_{student}$=3.99, $SD_{student}$=.97), but not for school analytics (H9e) (t(1287)=-1.652, p=.10, M_{parent}=3.36, SD_{parent}=1.04, $M_{student}$=3.24, $SD_{student}$=1.09).

For most of the data being used for LA, students evaluated it significantly more appropriate than parents. This includes performance data (H10a) (t(1287)=7.832, $p<.001$, M_{parent}=3.51, SD_{parent}=1.05, $M_{student}$=4.06, $SD_{student}$=.91), class group characteristics (H10c) (t(1287)=6.096, $p<.001$, M_{parent}=3.50, SD_{parent}=1.03, $M_{student}$=3.91, $SD_{student}$=.90) and school characteristics (H10d) (t(1287)=5.625, $p<.001$, M_{parent}=3.54, SD_{parent}=1.04, $M_{student}$=3.94, $SD_{student}$=1.02). For personal characteristics (H10b), however, parents and students did not differ from one another (t(1287)=-1.227, p=.22, M_{parent}=2.80, SD_{parent}=1.12, $M_{student}$=2.71, $SD_{student}$=1.08)

Equally, in terms of with which institutions the insights could be shared, students evaluated the school significantly more appropriate than parents did (H11a) (t(1287)=7.028, $p<.001$, M_{parent}=3.62, SD_{parent}=.97, $M_{student}$=4.07, $SD_{student}$=.79). There was no difference in appropriateness of sharing the insights with the learning platform (H11b) (t(1287)=-1.214, p=.225, M_{parent}=3.26, SD_{parent}=1.07, $M_{student}$=3.18, $SD_{student}$=1.11). Surprisingly, for sharing the insights with third parties, students evaluated it less appropriate than parents (H11c)(t(1287)=-3.241, $p<.001$, M_{parent}=2.49, SD_{parent}=1.17, $M_{student}$=2.23, $SD_{student}$=1.15)

Our hierarchical linear regression analyses showed that the effect of being a student or parent remained after adding gender as a predictor for the elements where there was a difference between the two to begin with. For some elements, gender is also a significant predictor (see appendix B). We conclude that students significantly differ from parents in their evaluation of the different elements of LA. The outcomes for each hypothesis of RQ2 can be found in Table 3.

	Hypotheses	Outcome
Goals	**H9a:** There is a difference between parents and students in how they evaluate student analytics focused on personal performance	V
	H9b: There is a difference between parents and students in how they evaluate student analytics focused on class performance	V
	H9c: There is a difference between parents and students in how they evaluate student analytics focused on personal drop-out risks	V
	H9d: There is a difference between parents and students in how they evaluate teacher analytics	V
	H9e: There is a difference between parents and students in how they evaluate LA school analytics	X
Data	**H10a:** There is a difference between parents and students in how they evaluate LA using personal school performance data	V
	H10b: There is a difference between parents and students in how they evaluate LA using personal characteristics	X
	H10c: There is a difference between parents and students in how they evaluate LA using class group characteristics	V
	H10d: There is a difference between parents and students in how they evaluate LA using school characteristics	V
Institutions	**H11a:** There is a difference between parents and students in how they evaluate that the insight of LA is accessibly by the school	V
	H11b: There is a difference between parents and students in how they evaluate that the insight of LA is accessibly by the learning platform	X
	H11c: There is a difference between parents and students in how they evaluate that the insight of LA is accessibly by a third party	V

Table 3: Overview of hypotheses and outcomes for RQ2

4 Discussion

In this study we amplified the voices of students and parents and investigated their evaluation of the appropriateness of the dataflows that are embedded in Learning Analytics (LA). We focused on students in higher secondary education as they often lack the agency, contrary to the often-investigated university students (Ifenthaler, 2016; K. M. L. Jones et al., 2020; Roberts et al., 2016; Tsai et al., 2020; Whitelock-Wainwright et al., 2020). Moreover, we also included the perspective of parents because for secondary school students, parents play an important role as they act as data-owners, are the bridge between the school and the home, and act as an important socialization agent who, next to the teacher, supports the education of their children.

The appropriateness and other attitudes towards the datafication and algorithmization in education is most often investigated through a holistic lens focusing on education in general or at a specific system containing a plethora of dataflows, platforms, and use cases (Pangrazio et al., 2022). This research, however, looked at how appropriate students and parents evaluate specific data flows within LA using the contextual integrity framework (Nissenbaum, 2004). Specifically, we focused on the goals of the LA, the data being used in the LA, and the institutions having access to the insights of the LA.

Comparing student analytics with teacher analytics, and school analytics, we found that student analytics are evaluated least appropriate, by parents and students. For parents, school analytics are also considered less appropriate than teacher analytics. According to multiple literature reviews, however, student analytics are by far the most implemented types of LA (Sghir et al., 2022; Sousa et al., 2021). Indeed, the most implemented LA systems are considered the least appropriate. Consequently, our findings could actively question if the norms of parents and students match the daily practices in schools. However, it is important to be mindful that, especially for students, the mean of the appropriateness of student analytics is still relatively high ($M= 3.43$ on a 5-point Likert-scale). Arguably, exploring different types of LA that are not only oriented at students could be beneficial for the education of students.

When zooming in on student analytics, the appropriateness of goals with a different impact (i.e., whether it just predicts the scoring of students or also predicts dropout) did not differ from one-another for students or parents. These insights contradict the insights from other contexts like digital contact tracing during COVID-19 (Martens et al., 2021) or other algorithmic systems in media, health or justice (Araujo et al., 2020), where the impact of the goals are found to be of paramount importance in the evaluation of these systems. For students, there was also no significant difference between the appropriateness of LA focusing on the individual or class level, countering the proposed distinction between the granularity of the insights of LA (K. Jones & Salo, 2018; Prinsloo et al., 2022; Taylor et al., 2016). Students perceive student analytics as equally (in)appropriate independent of their impact. For parents, however, there was a difference in appropriateness between the different aggregation levels confirming the importance of granularity for them (K. Jones & Salo, 2018; Prinsloo et al., 2022; Taylor et al., 2016).

When comparing students' to parents' perspective, it is noticeable that parents evaluate student analytics as significantly less appropriate than students. This could be due to parents being unable to sufficiently assess how student analytics are implemented, or due to their different backgrounds (Kong, 2018). For other types of LA, this difference is less apparent.

As standardized tests are increasingly being developed and used for different use cases (Akyol et al., 2021; Grek, 2009; Morgan & Ibrahim, 2020), the significant differences between the appropriateness of the different goals in our study suggests that we should remain vigilant on what goals we pursue with data that is collected in education. Our study shows that using specific data for one goal (i.e., student analytics) is not considered equally appropriate as using the same data for something else (i.e., school analytics), especially when the subject of these insight changes. The differences within a specific type of analytics (i.e., student analytics) is much less apparent. Moreover, as students on average evaluate the different goals of LA significantly higher than parents (except for school analytics), it could be the parents that resist future implementations of LA systems or other data collection practices as found by Hoel and Chen (2016). Especially in secondary education, the role of the parents should not be underestimated (Schneider et al., 2022). Parents of underage students are the owners of the (educational) personal data of their children (Hoel & Chen, 2016). Consequently, when implementing LA in secondary education the opinions and concerns of parents should be considered.

In terms of the data that could be used for LA, students and parents evaluate the traditional school related data (e.g., scoring) as most appropriate and more appropriate than using other types of data. Data that has traditionally been captured in the educational context is thus found more appropriate than other types of data, suggesting a more conservative stance of parents and students. These findings are also in line with Krein and Schiefner-Rohs (2021) as they argued that traditional school related data is most appropriate. When looking at personal characteristics, parents and students deem it much less appropriate to be used in LA. Interestingly, when looking at this type of data on a cohort level, like the class or school level, students and parents evaluate it much more appropriate and even as appropriate as using the school related data (i.e. student performance). While non individual student-data (i.e. school-data, class data) is much less used in LA (Sghir et al., 2022), our study thus found that they would be considered as appropriate or even more appropriate to be used. Arguably, LA systems could experiment with implementing other, coarse types of data to better capture the context of the student.

Students and parents match on their perceived appropriateness of with who insights from LA should be shared. Institutions that are less related to the educational context, are considered less appropriate to share LA insights with. The recipient of LA insights thus plays a role in the appropriateness of data flows in education (Nissenbaum, 2004). The school is evaluated as the most appropriate recipient, followed by the learning platform and then third parties. New actors, such as the learning platform or other third parties, are thus not necessarily evaluated as appropriate recipients of insights of LA (Lewis & Holloway, 2019). Meanwhile, schools employ these different actors, often without properly informing students or parents (K. M. L. Jones et al., 2020) into a a patchwork of platforms (Pangrazio et al., 2022). This could diminish students' and parents' trust in their educational institution (Slade et al., 2019; Tsai et al., 2020; Whitelock-Wainwright et al., 2020).

Despite this alignment between parents and students, sharing insights with the school is considered less appropriate by parents than students, as is sharing insights with a third party. These results suggest that depending on the role they fulfill, their evaluation of the institutions to share insights with differs. This reflects the complex interplay of expectations and concerns previous research found when investigating students' perspective towards LA (Ifenthaler, 2016; K. M. L. Jones et al., 2020; Slade et al., 2019; Viberg et al., 2018).

All these insights suggest that some practices of LA in education are deemed more appropriate than others for students and parents. Rather than looking into what is technologically possible in LA, we should understand what is perceived appropriate by *all* actors involved or at least raise awareness of the matter. A lower evaluation of appropriateness does not necessarily mean that we should refrain from applying these systems in education altogether. Educational institutions, however, are advised to meet the expectations of all actors as much as possible and include all their voices in their decision-making processes with and about LA.

We did find some red flags for both parents and students. Using personal characteristics in LA or sharing insights with a third parties is deemed inappropriate for parents and students alike. Based on this research it's advised to use the much coarser and deemed more appropriate characteristics on a class level. Moreover, the dataflows that are often directed to third parties in education (i.e., technical partners), should be minimized and justified towards parents and students following the minimization principle of the GDPR (GDPR, 2018).

Putting forward a contextual integrity approach (Nissenbaum, 2004), we were able to disentangle different defining elements in the dataflows within the educational context and evaluate their specific appropriateness. These fine-grained insights help to pinpoint and resolve specific issues students and parents have with LA. Zooming in on students and parents further allowed us to look at the differences between those who are directly experiencing the effect of algorithmic systems and those who carry a specific responsibility over this group but are not directly targeted themselves.

4.1 Future research & limitations

Current research focussed on a disentangled view on the voices of students and parents on the appropriateness towards data flows in LA, as they are often neglected in scholarly research. Future research could combine insights from students, teachers, parents, and management within the same scholarly context to help further contextualizing and interpreting these findings. This would enable a more layered analysis of how LA are evaluated.

This research focussed on a variety of goals, data, and institutions within different types of LA to gain a broad evaluation of the appropriateness towards these elements in LA. In the future, it could be beneficial to zoom in on specific use-cases of LA and distil all relevant elements within the dataflow of these use cases. This can be done using a vignette study design and would identify practical improvements to raise their appropriateness (e.g., Shilton & Martin, 2013). Moreover, future research could also get an even broader view by including more variation in the goals of LA and the types of data used to envelop the vast variation present in LA.

Because of the number of elements of the data flows within LA we wanted to compare and measure, single-item Likert-scales were used. More focused research, however, could put forward a more fine-grained and elaborate measure (e.g., include multiple items in a Likert scale or use a continuous scale).

We consider this study to be exploratory and not representative for all education types. Moreover, only gender was taken into account as an interpersonal characteristic. Hence, we advise future research to consider the diversity of students in their sample. In addition, it would be valuable to understand why students evaluate specific elements of the dataflows within LA as (in)appropriate.

5 References

Akyol, P., Krishna, K., & Wang, J. (2021). Taking PISA Seriously: How Accurate are Low-Stakes Exams? *Journal of Labor Research*, *42*(2), 184-243. https://doi.org/10.1007/s12122-021-09317-8

Amid, A., & Bangi, U. (2021). *Acceptance and use of massive open online courses: Extending UTAUT 2 with personal innovativeness*.

Araujo, T., Helberger, N., Kruikemeier, S., & de Vreese, C. H. (2020). In AI we trust? Perceptions about automated decision-making by artificial intelligence. *AI & SOCIETY*, 1-13. https://doi.org/10.1007/s00146-019-00931-w

Babbar, M., & Gupta, T. (2022). Response of educational institutions to COVID-19 pandemic: An inter-country comparison. *Policy Futures in Education*, *20*(4), 469-491. https://doi.org/10.1177/14782103211021937

Birnhack, M., & Perry-Hazan, L. (2020). School Surveillance in Context: High School Students' Perspectives on CCTV, Privacy, and Security. *Youth & Society*, *52*(7), 1312-1330.

Bishop, P. A., & Herron, R. L. (2015). Use and misuse of the Likert item responses and other ordinal measures. *International journal of exercise science*, *8*(3), 297.

Breiter, A. (2016). Datafication in Education: A Multi-Level Challenge for IT in Educational Management. In T. Brinda, N. Mavengere, I. Haukijärvi, C. Lewin, & D. Passey (Red.), *Stakeholders and Information Technology in Education* (pp. 95-103). Springer International Publishing.

Carifio, J., & Perla, R. (2008). Resolving the 50-year debate around using and misusing Likert scales. *Medical Education*, *42*(12), 1150-1152. https://doi.org/10.1111/j.1365-2923.2008.03172.x

Clow, D. (2013). An overview of learning analytics. *Teaching in Higher Education*, *18*(6), 683-695. https://doi.org/10.1080/13562517.2013.827653

Decuypere, M. (2021). The Topologies of Data Practices: A Methodological Introduction. *Journal of New Approaches in Educational Research*, *10*(1), 67. https://doi.org/10.7821/naer.2021.1.650

Dede, C., Ho, A., & Mitros, P. (2016). *Big Data Analysis in Higher Education: Promises and Pitfalls*.

Dong, C., Cao, S., & Li, H. (2020). Young children's online learning during COVID-19 pandemic: Chinese parents' beliefs and attitudes. *Children and Youth Services Review*, *118*, 105440. https://doi.org/10.1016/j.childyouth.2020.105440

Du, X., Yang, J., Shelton, B. E., Hung, J.-L., & Zhang, M. (2021). A systematic meta-Review and analysis of learning analytics research. *Behaviour & Information Technology*, *40*(1), 49-62. https://doi.org/10.1080/0144929X.2019.1669712

Farooq, M. S., Salam, M., Jaafar, N., Fayolle, A., Ayupp, K., Radovic-Markovic, M., & Sajid, A. (2017). Acceptance and use of lecture capture system (LCS) in executive business studies: Extending UTAUT2. *Interactive Technology and Smart Education*, *14*(4), 329-348. https://doi.org/10.1108/ITSE-06-2016-0015

Fritz, J., & Whitmer, J. (2019). Ethical Learning Analytics: "Do No Harm" Versus "Do Nothing". *New Directions for Institutional Research*, *2019*(183), 27-38. https://doi.org/10.1002/ir.20310

Gaftandzhieva, S., Docheva, M., & Doneva, R. (2021). A comprehensive approach to learning analytics in Bulgarian school education. *Education and Information Technologies*, *26*(1), 145-163. https://doi.org/10.1007/s10639-020-10261-w

Grek, S. (2009). Governing by numbers: The PISA 'effect' in Europe. *Journal of Education Policy*, *24*(1), 23-37. https://doi.org/10.1080/02680930802412669

Gursoy, M. E., Inan, A., Nergiz, M. E., & Saygin, Y. (2017). Privacy-Preserving Learning Analytics: Challenges and Techniques. *IEEE Transactions on Learning Technologies*, *10*(1), 68-81. https://doi.org/10.1109/TLT.2016.2607747

Hoel, T., & Chen, W. (2016). Privacy-driven Design of Learning Analytics Applications – Exploring the Design Space of Solutions for Data Sharing and Interoperability. *Journal of Learning Analytics*, *3*(1). https://doi.org/10.18608/jla.2016.31.9

Ifenthaler, D. (2016). *Student perceptions of privacy principles for learning analytics*. 16.

Jarke, J., & Breiter, A. (2019). Editorial: The datafication of education. *Learning, Media and Technology*, *44*(1), 1-6. https://doi.org/10.1080/17439884.2019.1573833

Jones, K. M. L., Asher, A., Goben, A., Perry, M. R., Salo, D., Briney, K. A., & Robertshaw, M. B. (2020). "We're being tracked at all times": Student perspectives of their privacy in relation to learning analytics in higher education. *Journal of the Association for Information Science and Technology*, *71*(9), 1044-1059. https://doi.org/10.1002/asi.24358

Jones, K., & Salo, D. (2018). Learning Analytics and the Academic Library: Professional Ethics Commitments at a Crossroads. *College & Research Libraries*, *79*(3), 304-323. https://doi.org/10.5860/crl.79.3.304

Kitto, K., & Knight, S. (2019). Practical ethics for building learning analytics. *British Journal of Educational Technology*, *50*(6), 2855-2870. https://doi.org/10.1111/bjet.12868

Kong, S.-C. (2018). Parents' perceptions of e-learning in school education: Implications for the partnership between schools and parents. *Technology, Pedagogy and Education*, *27*(1), 15-31. https://doi.org/10.1080/1475939X.2017.1317659

Krein, U., & Schiefner-Rohs, M. (2021). Data in Schools: (Changing) Practices and Blind Spots at a Glance. *Frontiers in Education*, *6*, 672666. https://doi.org/10.3389/feduc.2021.672666

Lewis, S., & Hartong, S. (2021). New shadow professionals and infrastructures around the datafied school: Topological thinking as an analytical device. *European Educational Research Journal*, 147490412110074. https://doi.org/10.1177/14749041211007496

Lewis, S., & Holloway, J. (2019). Datafying the teaching 'profession': Remaking the professional teacher in the image of data. *Cambridge Journal of Education*, *49*(1), 35-51. https://doi.org/10.1080/0305764X.2018.1441373

Mandinach, E. B. (2012). A Perfect Time for Data Use: Using Data-Driven Decision Making to Inform Practice. *Educational Psychologist*, *47*(2), 71-85. https://doi.org/10.1080/00461520.2012.667064

Martens, M., De Wolf, R., Vadendriessche, K., Evens, T., & De Marez, L. (2021). Applying contextual integrity to digital contact tracing and automated triage for hospitals during COVID-19. *Technology in Society*, *67*, 101748. https://doi.org/10.1016/j.techsoc.2021.101748

Morgan, C., & Ibrahim, A. (2020). Configuring the low performing user: PISA, TIMSS and the United Arab Emirates. *Journal of Education Policy*, *35*(6), 812-835. https://doi.org/10.1080/02680939.2019.1635273

Nicholas, J., Shilton, K., Schueller, S. M., Gray, E. L., Kwasny, M. J., & Mohr, D. C. (2019). The Role of Data Type and Recipient in Individuals' Perspectives on Sharing Passively Collected Smartphone Data for Mental Health: Cross-Sectional Questionnaire Study. *JMIR mHealth and uHealth*, *7*(4), e12578. https://doi.org/10.2196/12578

Nissenbaum, H. (2004). PRIVACY AS CONTEXTUAL INTEGRITY. *Washington Law Review*, *79*, 41.

Nissenbaum, H. (2019). Contextual Integrity Up and Down the Data Food Chain. *Theoretical Inquiries in Law*, *20*(1), 221-256. https://doi.org/10.1515/til-2019-0008

Pangrazio, L., Selwyn, N., & Cumbo, B. (2022). A patchwork of platforms: Mapping data infrastructures in schools. *Learning, Media and Technology*, 1-16. https://doi.org/10.1080/17439884.2022.2035395

Prinsloo, P., Slade, S., & Khalil, M. (2022). The answer is (not only) technological: Considering student data privacy in learning analytics. *British Journal of Educational Technology*, *53*(4), 876-893. https://doi.org/10.1111/bjet.13216

Ramírez-Rueda, M. del C., Cózar-Gutiérrez, R., Roblizo Colmenero, M. J., & González-Calero, J. A. (2021). Towards a coordinated vision of ICT in education: A comparative analysis of Preschool and Primary Education teachers' and parents' perceptions. *Teaching and Teacher Education*, *100*, 103300. https://doi.org/10.1016/j.tate.2021.103300

Ratner, H., Andersen, B. L., & Madsen, S. R. (2019). Configuring the teacher as data user: Public-private sector mediations of national test data. *Learning, Media and Technology*, *44*(1), 22-35. https://doi.org/10.1080/17439884.2018.1556218

Rice, M. E., & Harris, G. T. (2005). Comparing effect sizes in follow-up studies: ROC Area, Cohen's d, and r. *Law and Human Behavior*, *29*(5), 615-620. https://doi.org/10.1007/s10979-005-6832-7

Roberts, L. D., Howell, J. A., Seaman, K., & Gibson, D. C. (2016). Student Attitudes toward Learning Analytics in Higher Education: "The Fitbit Version of the Learning World". *Frontiers in Psychology*, *7*. https://doi.org/10.3389/fpsyg.2016.01959

Ruiz-Calleja, A., García, S., Tammets, K., Aguerrebere, C., & Ley, T. (2019). Scaling learning analytics up to the national level: The experience from Estonia and Uruguay. *Latin American Conference on Learning Analytics*.

Schneider, M., Teske, P., & Marschall, M. (2022). Choosing schools. In *Choosing Schools*. Princeton University Press.

Sclater, N. (2016). Developing a Code of Practice for Learning Analytics. *Journal of Learning Analytics*, *3*(1). https://doi.org/10.18608/jla.2016.31.3

Selwyn, N., Pangrazio, L., & Cumbo, B. (2021). Attending to data: Exploring the use of attendance data within the datafied school. *Research in Education*, 003452372098420\0. https://doi.org/10.1177/0034523720984200

Sghir, N., Adadi, A., & Lahmer, M. (2022). Recent advances in Predictive Learning Analytics: A decade systematic review (2012–2022). *Education and Information Technologies*. https://doi.org/10.1007/s10639-022-11536-0

Shahjahan, R. A. (2011). Decolonizing the evidence-based education and policy movement: Revealing the colonial vestiges in educational policy, research, and neoliberal reform. *Journal of Education Policy*, *26*(2), 181-206. https://doi.org/10.1080/02680939.2010.508176

Shilton, K., & Martin, K. E. (2013). Mobile Privacy Expectations in Context. *The 41st Research Conference on Communication, Information and Internet Policy*. TPRC 41. https://doi.org/10.2139/ssrn.2238707

Shore, C., & Wright, S. (2015). Governing by numbers: Audit culture, rankings and the new world order. *Social Anthropology*, *23*(1), 22-28. https://doi.org/10.1111/1469-8676.12098

Slade, S., Prinsloo, P., & Khalil, M. (2019). Learning analytics at the intersections of student trust, disclosure and benefit. *Proceedings of the 9th International Conference on Learning Analytics & Knowledge*, 235-244. https://doi.org/10.1145/3303772.3303796

Sousa, E. B. G. de, Alexandre, B., Ferreira Mello, R., Pontual Falcão, T., Vesin, B., & Gašević, D. (2021). Applications of Learning Analytics in High Schools: A Systematic Literature Review. *Frontiers in Artificial Intelligence*, *4*, 737891. https://doi.org/10.3389/frai.2021.737891

Takayama, K., & Lingard, B. (2019). Datafication of schooling in Japan: An epistemic critique through the 'problem of Japanese education'. *Journal of Education Policy*, *34*(4), 449-469. https://doi.org/10.1080/02680939.2018.1518542

Taylor, L., Floridi, L., & Van der Sloot, B. (2016). *Group privacy: New challenges of data technologies* (Vol. 126). Springer.

Tsai, Y.-S., Whitelock-Wainwright, A., & Gašević, D. (2020). *The privacy paradox and its implications for learning analytics*. 230-239.

Tsairidis, C., Kaltsidou, D., & Dimitriadis, E. (2020). Parents' perceptions over the use of New Technologies in Education. *International Journal of Humanities and Education Development (IJHED)*, *2*(2), 141-150. https://doi.org/10.22161/jhed.2.2.9

Viberg, O., Engström, L., Saqr, M., & Hrastinski, S. (2022). Exploring students' expectations of learning analytics: A person-centered approach. *Education and Information Technologies*, *27*(6), 8561-8581. https://doi.org/10.1007/s10639-022-10980-2

Viberg, O., Hatakka, M., Bälter, O., & Mavroudi, A. (2018). The current landscape of learning analytics in higher education. *Computers in Human Behavior*, *89*, 98-110. https://doi.org/10.1016/j.chb.2018.07.027

Whitelock-Wainwright, A., Gašević, D., Tejeiro, R., Tsai, Y., & Bennett, K. (2019). The Student Expectations of Learning Analytics Questionnaire. *Journal of Computer Assisted Learning*, *35*(5), 633-666. https://doi.org/10.1111/jcal.12366

Whitelock-Wainwright, A., Gašević, D., Tsai, Y.-S., Drachsler, H., Scheffel, M., Muñoz-Merino, P. J., Tammets, K., & Delgado Kloos, C. (2020). Assessing the validity of a learning analytics expectation instrument: A multinational study. *Journal of Computer Assisted Learning*, *36*(2), 209-240. https://doi.org/10.1111/jcal.12401

Williamson, B. (2017). *Big data in education: The digital future of learning, policy and practice*. Sage.

Williamson, B., Eynon, R., & Potter, J. (2020). Pandemic politics, pedagogies and practices: Digital technologies and distance education during the coronavirus emergency. *Learning, Media and Technology*, *45*(2), 107-114. https://doi.org/10.1080/17439884.2020.1761641

Winter, J. S., & Davidson, E. (2019). Big data governance of personal health information and challenges to contextual integrity. *The Information Society*, *35*(1), 36-51. https://doi.org/10.1080/01972243.2018.1542648

Zhu, S., Yang, H. H., MacLeod, J., Shi, Y., & Wu, D. (2018). Parents' and Students' Attitudes Toward Tablet Integration in Schools. *International Review of Research in Open and Distributed Learning*, *19*(4). https://doi.org/10.19173/irrodl.v19i4.2970

5.1 Appendix A – Operationalization of constructs

Construct	Survey-item	Answer options
1. Age	In what year were you born?	[open question]
2. Gender	What is the gender on your passport?	a. Male b. Female
3. Education degree (for parents)	What is your highest degree of education?	a. No degree b. Lower primary education c. Lower secondary education d. Higher secondary education e. Bachelor f. Master and PhD
4. Education type (for students	What education-type do you follow?	a. General secondary education b. Technical secondary education c. Vocational secondary education d. Art secondary education
5. Education year (for students)	In what school year are you at the moment?	a. 5^{th} year secondary b. 6^{th} year secondary c. 7^{th} year secondary
6. Appropriateness of goals of LA	**How appropriate would you evaluate a system with the goal of…** a. predicting your/your kids' personal school performance b. predicting the risk of you/your kid to drop-out of school c. predicting your class school performance d. evaluating how good your teacher does his/her job e. prioritizing the audit to the school	5-point Likert scale Totally inappropriate – totally appropriate

7. **Appropriateness of data used LA**	Think about the systems that you evaluated as appropriate: [shows systems scoring 3 or higher] **How appropriate would you evaluate it if these systems would use this data?** a. Your/your kids' scores on tests, exams, and exercises b. Your/your kids' characteristics (e.g., gender, age, home situation) c. Class group characteristics (e.g., gender ratio, education disadvantage indicator) d. School characteristics (e.g., gender ratio, education disadvantage indicator)	5-point Likert scale Totally inappropriate – totally appropriate
8. **Appropriateness of access to insights of LA**	Think about the systems that you evaluated as appropriate: [shows systems scoring 3 or higher] **How appropriate would you evaluate it if these systems would be accessible by…?** a. Your/your kids' school b. The learning platform of your/your kids' school (e.g., Google Classroom) c. A third party (e.g., a software company, technology firm)	5-point Likert scale Totally inappropriate – totally appropriate

5.2 Appendix B – Linear regressions with gender and being a parent or a student to predict elements in different dataflows in LA

Goals		Student analytics Personal performance		Student analytics Class performance		Student analytics Personal drop-out risk		Teacher analytics		School analytics	
		Std. B	t- value	Std. B	t- value	Std. B	t- value	Std. B	t- value	Std. B	t- value
H_0	Constant		54.5***		62.12***		50.65***		65.39***		51.086**
	Parent or Student	-.172	-6.27***	-.101	-3.63***	-.147	-5.34***	-.180	-6.58***	.046	1.652
H_1	Constant		48.87***		48.87***		45.54***		56.24***		44.24***
	Parent or Student	-.176	-6.45***	-.105	-3.80***	-.151	-5.51***	-.181	-6.58***	.045	1.621
	Gender	-.098	-3.57***	-.104	-3.76***	-.098	-3.56***	-.004	-0.883	-.019	-.697

*Table 1 linear regressions for goals, ***p<.001*

Data		Personal school scoring		Personal characteristics		Class group characteristics		School characteristics	
		Std. B	t- value	Std. B	t- value	Std. B	t- value	Std. B	t- value
H_0	Constant		65.86***		40.42***		64.90***		63.263***
	Parent or Student	-.213	-7.83***	.034	1.23	-.168	-6.10***	-.155	-5.625***
H_1	Constant		58.48***		36.84***		56.79***		55.594***
	Parent or Student	-.217	-8.00***	.030	1.07	-.170	-6.18***	-.158	-5.724***
	Gender	-.089	-3.29***	-.105	-3.77***	-.052	-1.89	-.062	-2.249*

*Table 2 linear regressions for data, ***p<.001, *p<.05*

Institutions		**School**		**Learning platform**		**Third party**	
		Std. B	t- value	Std. B	t- value	Std. B	t- value
H_0	Constant		72.209***		48.954***		31.82***
	Parent or Student	-.192	-7.028***	.034	1.214	-.168	3.24***
H_1	Constant		58.48***		42.37***		27.01***
	Parent or Student	-.194	-7.074***	.033	1.186	.091	3.264***
	Gender	-.033	-1.203	-.017	-.619	.017	.629

*Table 3 linear regressions for institutions, ***p<.001*