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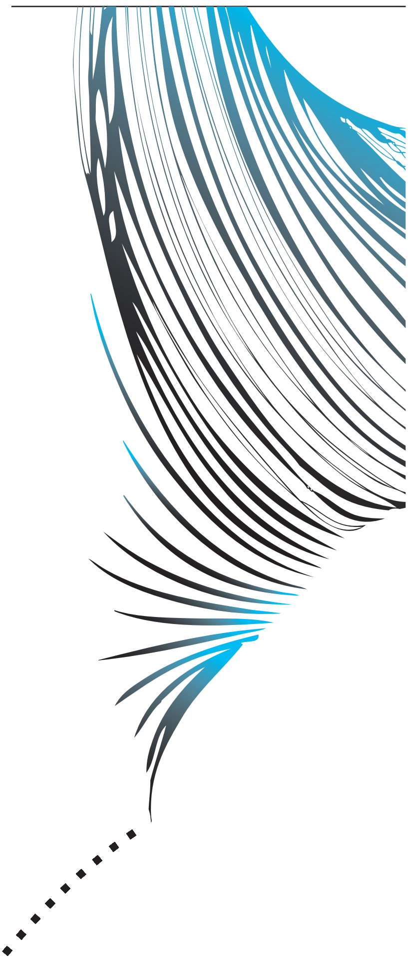

IN DIALOGUE WITH DATA IN EDUCATION

PROF. DR. KIM SCHILDKAMP

UNIVERSITY OF TWENTE.

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INAUGURAL LECTURE PROF. DR. KIM SCHILDKAMP

COLOPHON
Prof. dr. Kim Schildkamp

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Data algorithms, a curse or a blessing?

Is the era of report cards ending?

More assessments do not improve education

Prevent students from becoming the victims of a data-driven world

This is how schools in your neighborhood score

Educational field crucial in the advancement of artificial intelligence

People are more important than data

1. WHY DATA USE?

These are just a few of the (translated) headlines on data use in education that have made the Dutch news. Data use is trending, but that indeed begs the question whether data (algorithms) are a curse or a blessing and whether people are not more important than data. In this inaugural lecture, I will try to explain how data (algorithms) can be a blessing, but only if used in a certain way. I will also explain that it is not a matter of data versus people, but a matter of combining data with the wisdom, creativity and experience of people.

But let me start with the title of this inaugural lecture. I have used the word "dialogue" in the title. According to the thesaurus, synonyms are deliberation, conversation, discussion, chat and talk. The first question that we need to answer here is, why would we want to engage in this dialogue? The answer to this question is that studies have shown that decisions based on data are in general of higher quality than decisions based on intuition and anecdotal evidence (Ingram et al., 2004; Vanlommel et al., 2017). The reason for this is that although educators' intuition is very important (Sipman et al., 2019; Vanlommel et al., 2017), it is not always correct or enough (Kahneman & Frederick, 2005; Vanlommel & Schildkamp, 2019).

This is something we also discovered with our data team intervention (see section 4.2), where the results of one of our studies showed that a lot of assumptions about (the learning of) students in the school were not correct (Schildkamp et al., 2016). This even led to some of our data teams being called “MythBusters”[1].

It is important to stress here that although data are often associated with (standardized) assessment data and/or quantitative data (i.e., numbers), I use a much broader definition of data. Data can include any systematically collected relevant information about students, parents, schools, school leaders and teachers, and the community in which the school is located. This may include both qualitative (e.g., structured classroom observations) and quantitative (e.g., assessment results) methods of analysis (Lai & Schildkamp, 2016). It may include data on performance, but also data on other important indicators, such as well-being, health and socio-emotional development.

These data can be used in a process called data-informed decision making[2] or data use, for short: “systematically analyzing existing data sources within the school, applying the outcomes of analyses in order to innovate teaching, curricula, and school performance, and, implementing (e.g., genuine improvement actions) and evaluating these innovations” (Schildkamp & Kuiper, 2010, p. 482). However, I would also like to include here data that are collected less systematically. Teachers and students also collect information on a daily basis and often on the fly in a formative assessment approach: “part of everyday practice by students, teachers and peers that seeks, reflects upon and responds to information from dialogue, demonstration and observation in ways that enhance ongoing learning” (Klenowski, 2009, p. 264). Here, different forms of data are collected that can elicit evidence about student learning and achievement, which can then be interpreted by students and teachers, and used to guide instruction and learning in the classroom (Wiliam & Leahy, 2015).

School leaders, teachers, and students can make better decisions based on data, and these decisions are more likely to improve the quality of

[1] Fun fact: Jamie Hyneman, one of the makers of the television program MythBusters, received an honorary doctorate from the University of Twente in 2011.
[2] Also called data-driven decision making or data-based decision making.

education, in terms of teaching and learning. Different review studies (Grabarek & Kallemeyn, 2020; Marsh, 2012), including two meta-analyses (Ansyari et al., 2022; Spiele et al., 2020), indeed have shown that data use can lead to improved teaching, learning, and achievement in schools.

In this inaugural lecture, I will try to summarize what we know in the field with regard to the following themes: theories of action (section 2), data literacy (section 3), and supporting schools in the use of data (section 4). For each section, I will also address avenues for further research.

2. A DATA-USE THEORY OF ACTION

Several different data-use theories of action exist (e.g., Marsh 2012; Schildkamp, 2019; van Geel et al., 2016), but most of them include the following components: goal setting, data collection, data analysis, interpretation and making an action plan, implementing and evaluating the action plan.

2.1 GOAL SETTING

Data-use cycles usually start with a certain goal: Educators have a question, identified a problem that they want to solve and/or formulated a goal that they want to achieve (Marsh, 2012; Schildkamp, 2019). Studies have shown that it is helpful if the goals that are set are challenging, but also attainable, specific and measurable, as well as relevant (Locke & Latham, 2019; van Kuijk et al., 2016). For example, a goal could be to reduce the number of students in the entire school repeating a grade by 15%. Note here that data collection already plays a part in this step. If educators want to reduce the number of students repeating a grade by 15%, data are needed to establish how many students are currently repeating a grade.

Dialogue plays an important role in this step. Educators may benefit from establishing these school improvement goals together. However, different people may have different ideas and opinions about what these goals look like. From a policy perspective, school leaders may want to reduce grade repetition by 20% and teachers may think that 10% is more attainable given the current student population, whereas students, as well as their parents, may want to abolish grade repetition all together. Therefore, a dialogue between the different stakeholders that is supported by local school data is crucial in the whole process of goal setting. The outcomes of this process of deliberation, negotiation, and debate (Penuel & Shepard, 2016) should be a set of challenging, attainable, specific, measurable, relevant, and shared goals.

However, sometimes the process of data use starts with data and not with a goal. There are certain risks associated with starting with data. The first risk is 'drowning' in data. There are so many data sources out there that it is difficult to decide where to start. Moreover, for most educators, it is not very motivating to start with data. One of the lessons we have learned in one of our EU projects called "Using data for improving school and student performance" is that most educators do not get enthusiastic when confronted with data. In this project, our original plan was to start making data inventories in the schools we worked with. We soon abandoned this step, as this led to a lot of resistance towards data in those schools. As one of the teachers stated: "I became a teacher to work with children, not with data". However, when we started with questions such as "What are important goals for your school and/or classroom?" and "What are the problems you are currently facing?", this led to interesting, engaging and relevant dialogues. After that, we could introduce data as a tool to help educators achieve their goals and solve their problems.

Another risk of starting with data is that educators end up using all kinds of data that the school has been collecting for years, sometimes without checking the quality of these data. Some of these data may have been relevant several years ago, but might be less relevant now, as our society is constantly changing. As stated by Tulowitzki (2016), it is important to ask what goals data are being collected for, and why certain aspects are being measured.

A third risk is of starting with data is goal displacement (Lavertu, 2014). In our society, it is still the case that more data are being collected regarding goals that are easier to measure. For schools, the risk is that they focus solely on those goals for which they have data, thereby focusing on the measurable at the cost of other important goals. For example, an important goal for our current students is digital literacy. When I was in school, in the era of cassette tapes, this was not an important goal. Currently, this is a crucial competence for students, as we have also seen during the pandemic. However, a lot of schools may not (yet) have data available on the digital literacy of their students.

A further risk, based on anecdotal evidence so far, is that starting with data may lead to lower goals. This probably needs some explaining. In one of our data teams when we had just started with the intervention, the goal-setting phase and data-collection phase were still a little bit intertwined. Before looking at the data, teachers expressed in informal conversations that given their current student population, an average exam result of around 6.5 or 7 (on a scale from 1-10) might be feasible. They then looked at the data and discovered that the average score was 5.9. They then stated that this was a good enough score, rounded up to 6, so no follow-up action was deemed necessary. However, if they had set a shared goal of an average of 6.5 or even 7 before looking at the data, then they would have had to conclude that their goal had not been reached, so follow-up action would be necessary. Therefore, in our data team intervention, teams first set a challenging, attainable, specific, measurable, relevant, and shared goal before looking at the data.

2.2 DATA COLLECTION

Once the goals have been set, data can be collected to determine to what extent the goals have been reached. This is crucial, as these data can be seen as a form of feedback, and one of the key moderators of goal setting is feedback, which people need in order to track their progress towards these goals (Locke & Latham, 2019). If a certain goal has not been reached, data can be collected to find out why the goal has not been reached (Marsh, 2012; Schildkamp, 2019). As stated above, different types of data can be collected here, quantitative as well as qualitative data. Examples include (standardized) assessment data, classroom observations, and student voice data, for example, in the form of student surveys or interviews with students.

In our data team studies, student voices have been a valuable source of data. For example, when teachers interviewed low-achieving students, students said that they were spending too much time playing video games and too little time on studying, but they also told the teachers that they often did not understand the teachers' instruction, and that simply re-teaching the same content in the same way was not helpful. One of the students compared this with being on vacation, not understanding the language, indicating that you don't understand the language, and the reaction of the person that you are trying to talk to is to say the same thing again in the same way in the language you don't understand, but louder. Several studies have shown that student voice data can help with understanding and addressing the educational problems that schools are facing (Mitra, 2004; Yonezawa & Jones, 2007).

Dialogue between different stakeholders also plays an important role in determining what data to collect. Different people with different roles in the school (e.g., school leaders, teachers, students, parents) may have different ideas on possible causes of educational problems. A dialogue can help bring these possible causes to the table, and a dialogue is also required to make these possible causes measurable, in order to be able to determine what data need to be collected. Another source of evidence that can be used in this process is (scientific) literature. This is often referred to as research-informed teaching practice. Flood and Brown (2018, pp. 347-348) defined this as: "the process of teachers accessing, evaluating and applying the findings of academic research in order to improve teaching and learning in their schools". By making use of both local school data and evidence from scientific literature, educators can "combine the best of two worlds" (Brown et al., 2017).

2.3 DATA ANALYSIS, INTERPRETATION AND MAKING AN ACTION PLAN

Once the data have been collected, they need to be analyzed and interpreted (Marsh, 2012; Schildkamp, 2019). Only then can it be determined (why) a certain goal is or is not being reached. This is also called a sense-making process (Weick, 1998). This sense making is crucial, as the data in themselves are just numbers, pieces of audio, video and/or text. Implications regarding possible causes of problems and consequent solutions and actions are not immediately clear (Marsh, 2012; Vanlommel et al., 2017). Sense making is complex, and not a completely rational process (Kahneman & Frederick, 2005). As stated by Datnow et al. (2017), the same data may have different meanings for different people, and people filter data through their own lenses and experiences, in which intuition also plays an important role. Moreover, people are often inclined to use simpler, quick strategies that require less cognitive effort (Kahneman & Frederick, 2005). There is also a risk of biases playing a role, as when people sometimes try to fit data into a frame that confirms their assumptions and pre-existing beliefs without searching for alternative explanations, while ignoring data that do not match these prior ideas, and/or when their interpretation is greatly influenced by these prior beliefs (Kahneman & Frederick, 2005; Katz & Dack, 2014; Vanlommel & Schildkamp, 2018).

These risks can be mitigated by engaging in the process of sense making in a dialogue. Here educators can talk about what they think and feel when the results of the data analyses do not fit with their expectations, or they can discuss different interpretations of the same data set. By engaging in such a dialogue, these so-called cognitive conflicts (D' Mello et al., 2014) can be addressed and confirmation biases can be prevented (Katz & Dack, 2014). Engaging in a collective sense-making process in a dialogue allows educators to discuss and challenge each other's and their own underlying assumptions, beliefs and practices; they can discuss the results of the data analysis, can engage in collective interpretation; can confront the data with each other's ideas and biases; and they can revise their conceptions of teaching and learning (Bolhuis et al., 2016).

The analysis and interpretation phase should lead to an action plan with regard to the actions that are needed to achieve the goals set at the start of the data-use process. This is also another part of the data-use process where data are combined with educators' expertise. Action plans are often formulated based on the results of the data analysis and interpretation, educators' experience and knowledge, and sometimes also (scientific) literature (Marsh, 2012; Schildkamp, 2019).

2.4 IMPLEMENTING AND EVALUATING THE ACTION PLAN

Developing an action plan is not the same as implementing an action plan. Fidelity plays an important role here, meaning that the action plan is understood and performed as intended (Anderson, 2017). Implementing with fidelity an action plan that is often asking for substantive changes is not easy, as a classic study by Cohen (1990) demonstrated. In this study, a teacher, 'Mrs. Oublier', sees herself as successfully implementing a new reform, but the classroom observations tell a different story. An important question here is thus whether the action plan is actually being implemented as intended. Moreover, how is it perceived by its targets, often the students? This then leads to the question how tolerant the action plan is of deviations from the original plan. How many adaptations are possible without compromising the effectiveness of the action plan? Sometimes, too many adaptions lead to a "lethal mutation" (Brown & Campione, 1996 in McKenney & Reeves, 2019) of the action plan, resulting in its not achieving its goals anymore. In this step, data need to be collected to determine how the action plan is being implemented and received by the stakeholders, as well as whether the goal set in the beginning has been reached (Marsh, 2012; Schildkamp, 2019).

In conclusion, the data-use process consist of different components, and dialogue plays an important role in each of these components: the dialogue between different stakeholders when determining the goals; the dialogue on what data to collect; the dialogue with and between stakeholders and data in the analysis and interpretation (i.e., sense-making) phase, and the dialogue with and between stakeholders and data when it comes to planning, implementing, and evaluating actions. This calls for a process that can be called the dialogic use of data (Schildkamp, 2022, based on the dialogic use of exemplars in the formative assessment literature; e.g., Carless & Chan, 2017). The dialogic use of data provides educators with the opportunity for co-construction of learning based on data, and consequently with ideas to improve their practice and reach the goals they have set (Schildkamp, 2022).

Theoretically, this dialogic use of data is a straightforward and linear process. However, in reality, this process is complex, iterative, and at times messy (Marsh, 2012; Schildkamp, 2019). Sometimes educators collect data on a certain educational aspect and they discover that the quality of the data collected is low. Low-quality data lead to low-quality decisions, so new data need to be collected. Sometimes data show that a possible cause of a problem is in fact not a cause, so new hypotheses about possible causes of the problem under investigation need to be formulated and investigated. Sometimes, educators implement an innovation (implementing an action plan) and only then collect data to evaluate this innovation. Moreover, the process of data use is influenced by system-/policy-level characteristics (e.g., perceived accountability pressure), organizational-level characteristics (e.g., school leader support), data characteristics (e.g., data availability), and team and individual characteristics (e.g., data literacy; Datnow & Hubbard, 2016; Grabarek & Kallemeyn, 2020; Hoogland et al., 2016; Marsh, 2012).

2.5 A DATA-USE THEORY OF ACTION: AVENUES FOR FUTURE RESEARCH

The first research area that I would like to focus on with this chair is the importance of goal setting in the use of data. What are important goals for the future of our society and how are these established and defined?

Next to defining these goals, more insight is also needed on the whole process of goal setting. How can we support schools in developing and working on challenging, attainable, specific, measurable, relevant, and shared goals in a dialogue: a dialogue between different stakeholders, including school leaders, teachers, students and parents, but also perhaps a dialogue between educators and researchers in the form of research–practice partnerships (e.g., Farley-Ripple et al., 2018). Moreover, it is agreed-upon in the field that goal setting is a crucial aspect of the data-use cycle. However, in some models the data-use cycle starts with data collection and analysis (e.g., Marsh, 2012; van Geel et al., 2016), while in other models the process starts with goal setting (e.g., Schildkamp et al., 2016). It would be interesting to design an experiment to further investigate what the data-use process looks like when you start with data compared to when you start with goal setting. As mentioned above, risks are associated with starting with data. However, starting with data can also lead to discovering unexpected new connections between variables (Kool et al., 2015). This can lead to new insights, but there is also a risk of finding spurious correlations (Veldkamp et al., 2017).

The goals that educators have determine the data that need to be collected. This also implies that new measurement instruments need to be designed when new goals become relevant. For example, we have all witnessed the importance of digital literacy during the COVID pandemic, but most schools do not (yet) systematically collect data on the digital literacy skills of their students. We have also seen how important the wellbeing of students is, but this is again a goal for which most schools lack (high-quality) data. This leads to another important research topic: how we can support schools in collecting (and analyzing and interpreting) data on these types of goals, for example, by making use of (new) technologies, such as artificial intelligence (AI) and machine learning?

After the data have been collected, these data need to analyzed and interpreted. Another area for further research concerns the extent to which technology can take over (parts of) this process of data collection, analysis, visualization and storytelling, interpretation and making an action plan (see also section 4.4). Finally, more research is needed into how we can remove barriers to effective data use at these different levels of the system and how we can strengthen the enablers of data use.

3. DATA LITERACY

3.1 DATA LITERACY FOR EDUCATORS

Studies have shown that educators need a variety of knowledge, skills, and beliefs to be able to use data effectively (Datnow & Hubbard, 2016; Hoogland et al., 2016; Mandinach & Gummer, 2016). Educators need to be data literate to be able to use data. Data literacy was defined by Gummer and Mandinach (2015, p. 2) as:

> The ability to transform information into actionable instructional knowledge and practices by collecting, analyzing, and interpreting all types of data (assessment, school climate, behavioral, snapshot, longitudinal, moment-to-moment, and so on) to help determine instructional steps. It combines an understanding of data with standards, disciplinary knowledge and practices, curricular knowledge, pedagogical content knowledge, and an understanding of how children learn.

The core components of data literacy are: goal setting, collecting data, analyzing data, interpreting data, taking (instructional) action based on the data, and evaluating the consequences of these actions (Beck & Nunnaley, 2021; Kippers et al., 2018; Mandinach & Gummer, 2016; van Geel et al., 2016).

3.1.1 DATA LITERACY FOR EDUCATORS: AVENUES FOR FUTURE RESEARCH

Although there is general agreement in the field on these core components of data literacy, they need to be operationalized further (Ansyari et al., 2020; Mandinach & Gummer, 2016; Visscher, 2021). The data literacy continuum developed by Beck and Nunnaley (2021) that extends from pre-service to in-service teachers might be a starting point for further research. Moreover, it needs to be acknowledged here that psychological factors, such as attitude, social norms and self-efficacy also play a role (Ansyari et al., 2020; Prenger & Schildkamp, 2018). A possible approach to further untangling the concept of data literacy could be conducting a Delphi study to further operationalize the concept of data literacy for specific data sources.[3]

[3] As an example, one of our PhD students, Lucas Silva Didier, is currently conducting a Delphi study to untangle the concept of data literacy for a specific source of data: students’ perception of teaching quality.

Another approach, as also suggested by Visscher (2021), would be to conduct a detailed cognitive task analysis of expert behavior (in this case, the use of data). Wolterinck et al. (2022), for example, used this approach to study the knowledge and skills needed for formative assessment, and subsequently designed a professional development intervention targeting exactly this knowledge and skills. Her study showed that four closely related skills are required: (1) *preparing a lesson unit*, (e.g., determining learning goals); (2) *preparing a lesson* (e.g., analyzing students' learning progress); (3) lesson execution (e.g., sharing learning goals and success criteria); and (4) *lesson evaluation* (e.g., determining evidence-informed follow-up for the next lesson). Along with these skills, Wolterinck et al. (2022) found that teachers also need knowledge, such as pedagogical content knowledge, assessment knowledge, and knowledge of students' misconceptions.

3.2 DATA LITERACY FOR STUDENTS

Most studies in the use of data focus on the use of data by school leaders and/or teachers (e.g., Datnow & Hubbard, 2016; Kippers et al., 2018; Mandinach & Gummer, 2016). There is a lack of research into the use of data by students (Hoogland et al., 2016; Jimerson et al., 2016). However, students play an important role in the use of data (Hoogland et al., 2016; Marsh, 2012). How educators can involve students in the use of data can be described as ranging from students as passive to students as active stakeholders in the data-use process. An example of passive involvement includes the collection of student perceptions on the quality of teaching. Teachers can use these data to improve the quality of their instruction (Bijlsma et al., 2019). Students can also be actively involved in the data-use process, as when students are involved in analyzing, interpreting, and/or making an action plan, implementation and evaluation based on data with regard to improving the quality of teaching and learning in the school (Fielding, 2004; Kennedy & Datnow, 2011).

Students need to be data literate for this type of active involvement. Based on a comparison of nine different definitions of student data literacy, Wolff et al. (2016, p. 23) formulated the following definition, which has a lot of similarities with the definition of data literacy for teachers:

> Data literacy is the ability to ask and answer real-world questions from large and small data sets through an inquiry process, with consideration

> of ethical use of data. It is based on core practical and creative skills, with the ability to extend knowledge of specialist data handling skills according to goals. These include the abilities to select, clean, analyze, visualize, critique and interpret data, as well as to communicate stories from data and to use data as part of a design process.

Core components of this definition that are similar to the core components of data literacy for teachers include goal setting (in this case, finding an answer to a certain question), collecting data, analyzing data, interpreting data, and taking action based on the data.

There are several reasons why data literacy needs to be included in the curriculum of our schools. First, in the context of the digitalization of our society (e.g., personalized health and fitness apps on mobile phones collecting real-time data, data on social media, smart home applications), and the abundance of available data as a result of this, data literacy has become undeniably crucial (Gebre, 2018; OECD, 2019; Wolff et al., 2016). The OECD (2019), for example, stated that data literacy is a core foundation and a prerequisite for further learning. In order to inform their daily life inside and outside of school, students need to be able to access data, derive meaningful information from data, read, work with, analyze and argue with different types of data (e.g., quantitative, qualitative, visualizations), understand what data mean, draw correct conclusions from data, and make decisions; they must also recognize when data are being used in misleading or inappropriate ways (Gebre, 2018; Wolff et al., 2016).

Second, data literacy will also help students to make informed decisions and to exercise active citizenship (Gebre, 2018). Data here can be seen as a form of evidence, and students need to be able to evaluate the evidence that is presented and make judgements about the reliability of that evidence before making a decision (Wolff et al., 2016).

Moreover, some studies have even found that data literacy has become a prerequisite for success in learning (Erwin, 2015 in Gebre, 2018), as education, and especially post-secondary education, has become increasingly interdisciplinary and uses data as a part of scientific reasoning (Azevedo & Mann, in Gebre, 2018). This implies that students need to be aware of the different data sources that are available, their potential, and also their limitations (Gebre, 2018).

Furthermore, data literacy is important insofar as students need to be aware of their relationship to data, their role as a data source, and how this may affect them (Gebre, 2018; Kennisnet, 2021; Wolff et al., 2018). Students need to understand how their own data are being utilized, so that they can also make conscious decisions about what data to make (not) available (Wolff et al., 2018), taking into account how posting personal data on social media platforms, such as TikTok, YouTube and Instagram, influences their privacy (Kennisnet, 2021), for example.

Moreover, the prediction is that data literacy will be important for more and more jobs in the future, and being data literate increases one's chances on the labor market (Kennisnet, 2021). For example, data literacy is a core competence for data scientists; there already is a shortage of data scientists, and the prediction is that this shortage will increase (Wolff et al., 2018). Finally, students need to be aware of the role of data and algorithms in their (future) jobs (Kennisnet, 2021).

However, if we want data literacy to be part of the curriculum of schools, we need to further operationalize data literacy for students. At the student level, data literacy may be operationalized as being able to engage in formative assessment practices, and specifically in forms of peer- and self-assessment. Data literacy at this level is about students collecting data about their own work, to gain insight into their own abilities and to evaluate the quality of their own learning process and outcomes, identify possible problems, and take decisions on next steps (Harris & Brown, 2013; Liňán & Pérez, 2015; Panadero et al., 2016). This may also include comparing their work to that of their peers and providing peers with feedback[4]. The purpose is to use the collected data as a basis for feedback to promote learning and improvements in performance (Andrade, 2019). This implies that it is important that students actually use the collected data as feedback in order to monitor, plan and regulate their own learning. The use of data by students at the student level can provide students with more autonomy and ownership over their own learning process (Veldkamp et al., 2021).

At the classroom or curriculum level, data literacy is often operationalized in an entirely different way. Here, data literacy is often about students'

[4] The research topic of one of our PhD students, Priyanka Pereira.

competences with regard to using data in classroom assignments and projects, as is common in STEM (science, technology, engineering, mathematics) education. Gebre (2018), for example, found that students used a wide variety of data sources for a biology inquiry project. Students used survey data and experiment data for their self-chosen projects, as well as qualitative, image-related and observational data. Gebre (2018) concluded that this points to the potential for developing data literacy skills through (STEM) curricula.

At the school level, using the same general student data literacy definition, data literacy takes a different shape. All kinds of data are collected from students in schools. The role of students in schools is shifting from being the "object of change" to being the "creator of change", and students are moving from "positions of passivity to positions of action" (Yonezawa & Jones, 2007, p. 340). This implies that students are involved in the entire data-use process at the school level: goal setting, data collection, data analysis and interpretation, making action plans, implementation and evaluation. Several studies have shown that active student participation can help with understanding and addressing educational problems schools are facing, as student perspectives are central to understanding and addressing educational problems (Mitra, 2004; Yonezawa & Jones, 2007). Studies have shown that this helps educators see their school "with new eyes", and that this can help educators to improve the school for all students (Yonezawa & Jones, 2007, p. 328). Involving students in the data-use process also helps students to experience greater agency and self-worth, provides an authentic space for student voice and youth engagement, and helps students to develop a sense of belonging. Moreover, this helps to sustain motivation and engagement, which contributes to learning and achievement (Mitra, 2004; Yonezawa & Jones, 2007). Moreover, students can also develop data literacy by being involved in the use of data at the school level.

Finally, at the level of our society, data literacy can be operationalized differently, but again using the same definition as a starting point. Students provide a lot of data about themselves, for example, through various social media platforms. Students are often not aware of their role as a data source or the implications this might have (Gebre, 2018). If we want our students to be responsible and ethical data users, more attention needs to be paid to this. At the level of the society, data can also be seen as a tool for innovation. A lot of data are available, and this is only increasing as a result of the open data movement. The question here is how citizens can use these data to develop innovations, for example, within smart city applications. In these smart city applications, citizens can identify local problems and use data to come up with solutions that work in their own context, making them innovators who shape and implement solutions to urban problems instead of being only passive users and contributors of data (Wolff et al., 2016). We need to educate students so that they can become active citizens making use of all the potential that data have to offer.

3.2.1 DATA LITERACY FOR STUDENTS: AVENUES FOR FUTURE RESEARCH

The general view is that the foundation for data literacy needs to be developed in schools (Wolff et al., 2016). However, the importance of data literacy is mostly not yet reflected in the curricula of schools; in the best-case scenarios, there is attention to data literacy in the subject of mathematics. However, it has been suggested that teaching data literacy in a cross-curricular way would be more effective, incorporating it in different subjects (Wolff et al., 2016). An important question for further research is thus how to (further) incorporate student data literacy in the curriculum. This also requires designing approaches to support the teaching of data literacy.

Wolff et al. (2016) analyzed several existing approaches to supporting data literacy instruction, and concluded that a wide range of methods, resources and tools for teaching data literacy already exist. However, these approaches also have several weaknesses, such as a lack of a structured inquiry approach, the focus on only one very specific domain, or a lack of opportunities for students to phrase their own questions or goals. What these existing approaches also have in common is that they focus on the use of data at the classroom level, and to some extent at the level of our society. There seems to be less of a focus on the development of data literacy at the individual or school level.

Moreover, research is also needed with regard to how we can measure student data literacy. For teachers to be able to support students in developing data literacy, they need actionable data on their students' current level of data literacy, possible learning goals and success criteria, and they need insights into possible learning progressions with regard to data literacy. Only then will teachers be able to support their students in developing this core competence. Moreover, students themselves can also use this information to work on their own data literacy, thereby using data on their data literacy skills to monitor, plan and regulate their learning of data literacy.

4. HOW TO SUPPORT SCHOOLS IN THE USE OF DATA

Although engaging in a dialogue with data is promising for school improvement, it is a complex process. It is important to look at ways to support this process, to fully realize the benefits from the potential that data use in schools can offer. In this final part of this inaugural lecture, I would like to discuss several ways to support data use in schools: (1) professional development in the use of data, (2) professional learning networks (as a form of professional development), (3) organizational readiness for the use of data, and (4) the use of technology to support data use. These are all avenues for future research, as I will discuss below.

4.1 PROFESSIONAL DEVELOPMENT IN THE USE OF DATA

An important question to be answered here is to what extent teachers are trained in the use of data. Data literacy or data use is not specifically mentioned in the performance standards for Dutch teachers (Bolhuis et al., 2017; Ministerie van Onderwijs, Cultuur & Wetenschap, 2017). The word "data" is not even mentioned once in these performance standards. However, at the same time, attention to data use is increasing in the curricula of pre-service teacher training. Bolhuis et al. (2017) found, for example, that data use was part of the teacher training curricula of 93% of the teacher training colleges for primary education they studied[5]. However, there were large differences in how much attention was paid to data use. They found that in 41% of the colleges, time spent on teaching data use was about 1-2 ECTS (28-56 hours), in 26% of the colleges it was 3-5 ECTS (84-140 hours), in 22% it was 6-10 ECTS (168-280 hours), and in 12% it was more than 10 ECTS (more than 280 hours) throughout the entire program.

[5] N=10 (22% of the teacher training colleges for primary education in the Netherlands, at the time of this study).

The way data use was taught also differed in teacher training colleges, and not all the components of the data-use process received attention. For example, data quality did not seem to receive a lot of attention (included at only 50% of the teacher training colleges), and 25% of the teacher training colleges did not spend time on data analysis (Bolhuis et al., 2017). This raises questions with regard to the quality of the data-use process in these cases. Others have also concluded that there is still a lot of room for improvement in terms of the way data use is (or is not) trained at teacher training colleges (Bron et al., 2013). This leads to the question, how can data use become a solid part of teacher training? We need to lay the foundation there for data use by our future teachers and combine that with the total package of knowledge and skills that teachers need in order to use data, including, for example, pedagogical content knowledge (Mandinach & Gummer, 2016; Visscher, 2021).

However, we also need to acknowledge that teacher training curricula are already facing problems with regard to an overloaded curriculum. Not only has data use become important, but topics such as educational innovation (with the use of ICT) have also become more important[6]. Moreover, data use is complex and requires a lot of practice. Gelderblom et al. (2016), for example, found that Dutch teachers' process of data-based decision making was superficial at several schools. Data were not used in a way that would lead to improving learning outcomes. Therefore, although the foundation needs to be laid during teacher training (pre-service professional development), in-service professional development also plays an important role.

However, professional development interventions do not always lead to the desired effects. Some studies have found positive effects of data use professional development interventions (e.g., Keuning et al., 2019; Poortman & Schildkamp, 2016; van der Scheer & Visscher, 2018; van Geel et al., 2016; van Kuijk, 2014); others have found no or ambiguous results (Randel et al., 2016; Staman et al., 2017). However, overall, the results seem to be promising. In a meta-analysis including 10 studies, Ansyari et al., (2022)

[6] See, for example, the Dutch acceleration plan for educational innovation with ICT: https://www.versnellingsplan.nl/en/). Moreover, one of our PhD students, Andrea Kottmann, is currently studying innovations in higher education.

found a significant positive effect on student achievement, with an effect size of 0.17. In another meta-analysis, Spiele et al. (2020) quantitatively synthesized the results of 27 studies on the impact of data use professional development interventions on student achievement. They found a medium-sized positive effect on student achievement (*g* = .37); however, there was significant heterogeneity in the results. They concluded that although it seems that data use professional development interventions can improve education, more research is needed into effective data use professional development interventions and what makes these interventions effective.

Although several reviews exist on what the building blocks for effective professional development in general are (e.g., Schildkamp et al., 2021; van Veen et al., 2012) and toolkits have been developed[7], consensus on characteristics of effective data use professional development interventions has not yet been established. Moreover, the building blocks are often very general (e.g., active learning, longer duration, ownership), which makes them hard to translate into an effective professional development intervention. Furthermore, these building blocks may differ for different subjects, different types of data, and different contexts. Although knowledge exists with regard to proven effective data-informed decision making interventions (e.g., Keuning et al., 2019; Poortman & Schildkamp, 2016; van der Scheer & Visscher, 2018; van Geel et al., 2016; van Kuijk, 2014) further research is needed to establish what the specific building blocks are for effective data use professional development interventions in different contexts (e.g., primary, secondary, vocational and higher education). Moreover, another challenges lies in the scaling up and sustainability of these intervention, from "research project schools" to data use as an organizational routine in a large number of schools. Solutions that I would like to further investigate may include the offering of blended professional development programs, which take place partly in the school and partly online. Another solution might be found in the use of technologies that can take over part of the data use process in schools (see section 4.4).

[7] https://www.versnellingsplan.nl/en/Kennisbank/toolkit-building-blocks-effective-lecturer-professional-development/

4.2 PROFESSIONAL LEARNING NETWORKS

One effective building block for professional development seems to be collaboration (e.g., Darling-Hammond et al., 2017; Gast et al., 2017; Schildkamp et al., 2021; van Veen et al. 2010). Several data use studies have also pointed to the importance of collaboration (e.g., Ansyari et al., 2022; Datnow & Hubbard, 2016; Hoogland et al., 2016; Marsh, 2012; Visscher, 2021). A specific form of collaboration occurs in professional learning networks (PLNs; Brown & Poortman, 2018; Prenger et al., 2021). Brown and Poortman (2018, p. 1) defined PLNs as: "any group who engage in collaborative learning with others outside of their everyday community of practice in order to improve teaching and learning". According to Hargreaves and Shirley (2009), collaboration in PLNs can lead to effective changes in teaching and learning. The data team intervention is an example of a professional development intervention focused on the use of data in PLNs.

A data team (Schildkamp et al., 2014) is a PLN consisting of six to eight educators who use data to solve a certain educational problem. Examples of these problems include problems at the level of the school (e.g., grade repetition) or classroom (e.g., low mathematics achievement). Based on data, a data team investigates possible causes of the problem, and based on data, they develop and implement solutions to solve the problem. Studies have shown that working in a data team can increase data literacy, and lead to increased data use, changes in instruction, assessment and the curriculum, and ultimately to increased student achievement (Ebbeler et al., 2016, Kippers et al., 2018; Poortman & Schildkamp, 2016; Schildkamp et al., 2016).

Next to the effects of the data team intervention, sustainability of the data team intervention has also been studied. Often, the sustainability of interventions is not studied (Datnow, 2005), or if studied the conclusion is that the innovation has not become an organizational routine (Wiltsey-Stirrnam et al., 2012). Sustaining innovations is a challenge (Hargreaves & Fink, 2012), also when it comes to data use professional development interventions (Hubers et al., 2017). However, as data use should be a continuous and iterative process in schools, sustainability is crucial. Tappel et al. (2022) studied the sustainability of data use (in data teams) in schools and identified four clusters of sustainability: (1) not sustainable (*n* = 7, 24%) where no examples of data use or data teams could be found; (2)

sustainable for the method of the data team intervention (*n* = 7, 24%), where only data team members worked towards the goal of the intervention, but data use was not visible anywhere else (e.g., hardly visible in policy documents); (3) sustainable for the goals of the data team intervention (*n* = 9, 31%), where schools did not work with the data team method anymore, but worked cyclically on educational improvement using data; and (4) sustainable for the goals and the method (*n* = 6, 21%), where the entire school location worked on the underlying goal of the intervention, and data teams were still active and following the method.

The data team intervention has been studied extensively, and more than a decade of research is now available. Yet, methodological challenges still exist in studying the effects and sustainability of data use interventions such as data teams. For example, linking data use PLN interventions to improved instructional decision making in the classroom as well as improved student achievement via a randomized controlled trial is complex (e.g., linking all the different components); time-consuming (e.g., observing the quality of instruction in many classrooms); and sometimes not even feasible (e.g., because schools do not want to participate in a control group).

Poortman et al. (2022) concluded, based on several reviews, that more rigorous research is needed in order to build evidence supporting the positive impact of PLNs (such as data teams) on teaching practice and outcomes for student. Poortman et al. (2022) suggested that program theory (i.e., theory of action) and theory-driven program impact pathway (PIP) analysis (i.e., explicitly mapping and assessing the mediating steps between the inputs and outcomes of the program, following a causal logic) might be a way forward. For example, Ansyari et al. (2022) made a start with such a theory of action based on a systematic literature review including the characteristics of the professional development intervention, the process of data use in schools and the influential factors, and the effects of this process on teacher quality, instructional decision-making, and student outcomes. Poortman et al.'s (2022) recommendation needs further follow-up if we want to gain more insight into why certain data use professional development interventions do or do not work, and under which circumstances, in which context, and for which stakeholders.

For example, Hebbecker et al. (2022) found in their study on the effectiveness of a data use professional development intervention that their intervention did increase student achievement, but they did not find an effect on instructional decision-making. They concluded that this may have been due to the way instructional decision-making was measured (i.e., self-report instead of observation). However, it may also have been due to what might be a missing link in the data use research so far. Several models (e.g., Ansyari et al., 2022; Hebbecker et al., 2022, Poortman & Schildkamp, 2016; van Geel et al., 2016) propose that data use leads to changes in teachers' attitudes, knowledge and skills (e.g., increased data literacy), which leads to instructional changes, which leads to better student outcomes. However, one could argue that a missing link here is how students perceive the instructional changes and how they respond to these changes. Positive responses to instructional changes are more likely to lead to better student outcomes. For example, Christ et al. (2022) found in their study using TALIS data that teaching quality was not directly related to student achievement, but was related to mediators, such as students' use of opportunities provided to them by their teachers, including time on task, depth of processing and need satisfaction.

Poortman et al. (2022) also provided recommendations with regard to how to study the work of PLNs such as data teams. Poortman et al. (2022) stated that technologies such as artificial intelligence (AI) can be used to gain more insight into specific PLN processes and their (in)effectiveness in terms of predicting their effects on student achievement. For example, as suggested by Poortman et al. (2022), text mining and machine learning could be used to make in-depth research into the PLN enactment processes (such as the use of data in data teams) more efficient, valid and reliable[8]. These new technologies can not only be used to support the data use process in schools, but could also support researching the use of data (in PLNs) in schools.

4.3 ORGANIZATIONAL READINESS FOR THE USE OF DATA

Data use does not happen in isolation. The characteristics of the school organization are a large influence on the use of data in schools (Grabarek & Kallemeyn, 2020; Schildkamp et al., 2017). School culture plays an

[8] We are currently exploring this further in a project with the Stichting Carmel College, together with our junior researcher, Myrthe Lubbers.

important role, and data-use processes benefit from cultures that are aimed at continuous improvement, innovation, and collaboration (for example, in PLNs). Clear structures, routines and responsibilities also can facilitate data use. Data use can be further stimulated if teachers feel they have enough autonomy to make changes based on data and if teachers feel that their profession is being respected. Moreover, support, time and means need to be available for the use of data (Grabarek & Kallemeyn, 2020; Hoogland et al., 2016; Marsh, 2012). In terms of these means, effective data use requires the availability of accessible, relevant, and timely high-quality data. The use of digital systems, such as student monitoring systems, can support the use of data, but only if these systems are aligned with the goals of the teachers and school leaders (Grabarek & Kallemeyn, 2020; Hoogland et al., 2016; Marsh, 2012).

School leaders also play a crucial role in the data-use process. As data users themselves, school leaders need to engage in a dialogue with different stakeholders (e.g., the school board, municipality or district they fall under, parents, teachers) to be able to balance the various goals of these stakeholders with the vision of the school. Teachers are an important partner in this process of goal setting. School leaders may also want to translate policies into specific goals and sometimes prioritize certain goals. It is important that the goals are shared within the school and that there is commitment and a sense of urgency to work on these goals. School leaders can then determine together with other stakeholders what data to collect. By engaging in collective sense-making and developing of action plans, school leaders can also influence the process of sense making, and can make sure improvement actions are implemented and that data use is seen as an important process contributing to school improvement (Coburn, 2006; Schildkamp, 2019).

School leaders can also support, champion, and facilitate data use by teachers in their school. Studies (e.g., Datnow & Hubbard, 2016; Hoogland et al., 2016; Schildkamp & Datnow, 2022; Schildkamp et al., 2019; van den Boom-Muilenburg et al., 2021) have shown, that there are several leadership building blocks for effective (sustained) data use, including: facilitation of such use in terms of time, access, and technology; developing a vision, mission, and goals that are clear, consistent, and coherent; creating a safe environment to use data; being a role model; providing intellectual and emotional support; monitoring the use of data in schools; and communicating and networking.

Several tools are available for school leaders and other stakeholders to support the use of data in schools. Van den Boom-Muilenburg et al. (2021) developed a reflection tool[9] that educators can use to analyze the leadership necessary for sustainable implementation of innovations such as the use of data. Another tool that schools can use to determine their organizational readiness is the Quick Scan for Education Data[10]. With this tool, an organization can determine how mature it is in terms of safe and reliable data use. The tool has the following main categories: Strategy & Policy (the way in which the strategies and policymaking process around data are organized); People & Culture (the value of an employee for the school); Organization (the extent to which the school organizes and rolls out data centrally); Governance & Guidance (the way in which the school works on governance and management based on data); Information Technology (how the school gives technical shape to education data products, for example, through a central portal). Schools can determine how far they are in their development for each of these levels.

Finally, an important aspect with regard to organizational readiness has to do with General Data Protection Regulation (GDPR) guidelines, dealing with aspects such as security and privacy. Data ethics is also a crucial part of data use; it includes security and privacy, but it is broader than that. According to Mandinach and Jimerson (2016, p. 12), data ethics is “the ability not only to use appropriate data for appropriate purposes, but to apply reasons that prioritize the long-term benefit of students”. The “Privacy and Ethics Reference Framework for Education Data”[11] is a framework that focusses on the use of data in a careful, secure, and responsible way that is in line with the values within the education sector. However, although several tools and frameworks have been developed, I would like to conduct further research into how we can prepare school organizations for the efficient and effective use of data (technologies) to improve education.

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[9] https://pro-u.reflectiontool.utwente.nl/en
[10] https://www.versnellingsplan.nl/en/Kennisbank/quickscan-education-data/.
[11] https://www.versnellingsplan.nl/en/Kennisbank/privacy-and-ethics-reference-framework-for-education-data/

4.4 TECHNOLOGY AND THE USE OF DATA

Technology can support the use of data in schools in several (related) ways. First, technology can help in the collection of data, and can also generate (massive amounts of) data, as we have seen during the COVID pandemic. Engaging in online, hybrid or blended[12] learning generates a lot of data. Examples include time spent on a certain platform, number of clicks, number of comments provided on a discussion forum, the number of (parts of) online videos that have been watched, attendance, and achievement data. Moreover, technologies such as adaptive learning technologies are also becoming more widespread (Molenaar, 2022). Students engage with these technologies, which also generates data.

Second, technologies are available that can help visualize data, so that data are easier to interpret, letting the data tell the story. Examples here include infographics, dashboards displaying all kinds of data in a visual manner, and gamified data (Akcaova et al., 2022).

Third, technology can also assist in the actual use of these data. An example is learning analytics[13], in which data about learners and their contexts are collected and analyzed, and used to measure and understand the learning processes and performance of (groups of) students. This information can lead to insights into the effectiveness of teaching practices; this information can then be used to improve education (Jülicher, 2018). If we take this one step further, in which the analyzed data also lead to a decision or form of action provided by the technology (e.g., feedback, providing a student with a next assignment, a grade), this can be seen as artificial intelligence (AI) in education (Walker & Baten, 2022). Many definitions of AI exist. The Dutch National AI Coalition has developed several AI courses (including one for education[14]), and they use the following broad definition for AI: "intelligent systems that can perform tasks independently in complex environments and improve their own performance by learning from experience" (Dutch National AI Coalition, 2022).

[12] For more information on blended learning see for example the work of Linlin Pei and: https://www.versnellingsplan.nl/Kennisbank/toolkit-blend-je-onderwijs/

[13] For more information see for example: https://www.versnellingsplan.nl/en/Kennisbank/field-lab-for-professionalization/field-lab-learning-analytics/

Examples of applications of these technologies include: adaptive practice programs that detect errors, analyze misconceptions and provide students with the next assignment based on their progress; programs that automatically grade students' work; programs that provide students with automatic feedback; dashboards that provide teachers (and students) with information on students' activities, correct and incorrect answers, progress and performance; programs that diagnose language and speech problems based on written and/or oral texts; virtual teaching assistants, for example, in the form of a chatbot; and intelligent tutoring systems (Molenaar & Knoop-van Campen, 2019; Onderwijsraad, 2022; Walker & Baten, 2022).

Another example here relates to formative assessment practices in classrooms. An already prevalent practice is the use of online quizzes. AI can not only automatically analyze the right and wrong answers for multiple-choice questions, but can also analyze pieces of text inputted by students and even advise teachers on how to respond to certain answers (McMurtrie, 2018, in Onderwijsraad, 2022). A more advanced form of technology-supported formative assessment is the use of augmented reality glasses. Teachers look at their classroom through these classes and are presented with real-time data on their students who are working in a digital learning environment. For example, they receive information on which of their students need extra help or attention (Holstein et al., 2019, in Onderwijsraad, 2022; Wise & Jung, 2016, in Onderwijsraad, 2022). These kinds of technologies could enhance the use of formative assessment practices in classrooms, and could also be incorporated in professional development interventions focused on formative assessment (e.g., de Vries et al., 2022; Gulikers et al., 2021; Wolterinck et al., 2022), so that teachers can practice with these types of technologies.

AI technologies are used the most in adaptive learning systems, generally in primary and secondary education. However, other applications, such as the use of software that automatically evaluates students' work, is also getting more common in both vocational and higher education (Onderwijsraad, 2022). Different types of data, such as log files, mouse movements, keyboard entries, and eye-tracking data can be used for advanced tracking

[14] https://onderwijs.ai-cursus.nl/home

of learners and their environment. Once gathered, these data are analyzed to diagnose students' current states and predict future development. Thereafter, an action plan needs to be developed to support the students' learning based on the interpretation of their needs. This last step is very complex, as there are endless possible response patterns, different needs, and only limited evidence as to which interventions are most effective (Molenaar, 2022). Molenaar distinguished between three types of actions based on data: (1) step-type actions, in which students receive feedback on how to proceed correctly with a certain (part of a) task, for example, based on an analysis of misconceptions; (2) task-type actions, in which the best next task is selected for the student; or (3) curriculum-type actions, in which the entire organization of instructional topics is adjusted to the needs of the student.

An advantage of the use of technology in the data-use process is that it can take over certain of teachers' tasks, for example, in terms of data collection, analysis and (partial) interpretation. A lot of adaptive learning technologies have already been developed for foundational skills, which allows for more efficient teaching of such skills (Faber et al., 2017). At the same time, this frees up time for working on more complex skills such as problem-solving, and for providing students with personal attention (Molenaar, 2022; Onderwijsraad, 2022). Moreover, the use of technology to support data use, for example, in the form of adaptive practice programs, can enrich the classroom, as students receive more (specific) feedback more often (Onderwijsraad, 2022). A study by Keuning and van Geel (2021) also showed that by using adaptive learning systems, teachers have faster and more up-to-date information about their students' progress, and can use this information during the lesson to adapt their instruction to the students' needs more quickly and accurately.

Technology is able to take over more and more tasks in education. This leads to the question of what tasks technology should and should not take over. Molenaar (2022) developed a model identifying the six levels of automation of personalized learning that can be used as a starting point for answering this question. The basic idea is the expectation that more data streams will be used in the transition to full automation. In level 0 there is no automation; the teacher is completely in control. In level 1 (teacher assistance), technology supports teachers in the organization of the learning environment. The technology does not control anything here.

Examples here include electronic learning environments and learning management systems. In level 2 (partial automation), technology controls specific organizational tasks, such as providing students with automated feedback. At this level, teachers are still completely in control and monitor the functioning of the technology, for example, through dashboards. In level 3 (conditional automation), technology takes over more organizational tasks in the learning environment. The technology signals when teacher control is needed, and the teacher monitors incidentally. In level 4 (high automation), technology controls most tasks automatically. The technology can request teacher control, but teacher control and monitoring are not required for specific tasks. Finally, in level 5 (full automation), technology controls all tasks automatically. The role of the teacher is completely taken over. However, the question here is how feasible and desirable this is (Molenaar, 2022). Another question that we need to answer here is what the role of the student is for each of these levels. And perhaps we need to develop a similar model as developed by Molenaar (2022) but then taking students and student control as a starting point.

Molenaar's (2022) model is also helpful in thinking about what tasks technology should (not) take over when it comes to the entire data-use process. When it comes to goal setting, I think most people would agree that we should leave this up to educators and students. When it comes to data collection and data analysis, technology could perhaps take over a large part. However, when we get to the level of interpretation and developing an action plan, this is less straightforward. Progress is being made with regard to technologies that can suggest the best next instructional steps for a teacher (based on data and scientific literature).

A possible technique that could be used here, and that we are currently experimenting with is a technique called "digital twins"[15]; developing student profiles based on data (Fischer et al., 2020). By matching students to their digital twin from previous cohorts, we already know what kind of education they received and what the results were. We can then also diagnose possible learning problems and predict based on their digital twin how they will develop and which intervention will work best for them (Fischer et al., 2020). Based on these profiles and scientific literature on

[15] NRO project "Digital twins to the rescue", led by Bernard Veldkamp, project nr. 40.5.20400.015

proven effective interventions with similar students, teachers can select the intervention that matches the needs of the student best (Valiandes, 2015; Tomlinson, 2014). There is already some evidence that using these digital twins can be useful for adapting instruction to the needs of the students (Pardos et al., 2017; Clement et al., 2015), but this needs further investigation.

Although these technologies can support the collection, analysis and interpretation of the data, it is still the teachers who have to use these interpretations, and also sometimes adjust the interpretations based on their knowledge of the context and the students, in order to make effective instructional changes in the classroom (Deunk et al., 2018; Keuning & van Geel, 2021; Molenaar, 2022; Onderwijsraad, 2022).

5. CONCLUDING REMARKS

I would like to end this inaugural lecture with a couple of cautions concerning (technology and) the use of data. First, the effects of data use naturally depend on how the data are (not) being used. Teachers may not want to use data, or use data only in a symbolic manner, or misuse or even abuse the data. The goal is that data are being used instrumentally for making changes in school and in classrooms (Farley-Ripple et al., 2018; Weiss, 1998). However, data are often used in a more conceptual way that influences educators' thinking (Farley-Ripple et al., 2018; Weiss 1998), but does not necessarily translate into concrete changes. Sometimes data are manipulated to attain specific power or personal goals (Farley-Ripple et al., 2018), and sometimes data are used in a strictly symbolic way to conform with certain accountability pressures (Farley-Ripple et al., 2018). Finally, sometimes data are misused (e.g., wrong interpretations leading to ineffective decisions) or even abused, when data are only used for "teaching to the test" purposes or when attention is directed solely towards the students on the verge of achieving some kind of threshold or benchmark (Booher-Jennings, 2005).

Moreover, we do not have (high-quality) data (yet) on certain goals that are important in our schools. The data and algorithms available also sometimes provide an incomplete picture of the reality in schools and classrooms. If these are used without combining them with the knowledge and experience of educators, this may lead to narrow forms of education and negative effects on the quality of education (Onderwijsraad, 2022).

Furthermore, if technology takes over too much of the teacher's role, this may lead to teachers feeling that they are being pushed out-of-the-loop (Holstein et al., 2020, in Molenaar, 2022), and they may experience a lack of autonomy (Molenaar, 2022; Onderwijsraad, 2022), feeling like slaves of the system and/or the data. Related to this is that data-use systems currently are sometimes black boxes for educators, in which it is unclear what type of analyses have led to what type of decisions. Algorithms need to be explainable to educators, at least to some extent, for example, that a certain type of feedback in a system is related to certain types of misconceptions. This prevents educators from feeling out-of-the-loop (Baker, 2016, in Onderwijsraad, 2022).

Data use can negatively impact students, who may feel like they are constantly being watched and judged and are under continuous surveillance (Williamson, 2021, in Onderwijsraad, 2022). An often-heard phrase is that students are then reduced to numbers instead of actual human beings. Moreover, although (technologies supporting the use of) data can lead to more equity in education, they can also reinforce inequality, and even profile, stigmatize, and discriminate against certain (groups of) students (Datnow & Park, 2018; Onderwijsraad, 2022; Veldkamp et al., 2021). As Datnow and Park (2018, p. 149) stated: "The use of data for tracking, long-term ability grouping, and placement is of particular concern, as it can serve to reinforce hierarchies among students." High-performing students, for example, benefit more from adaptive practice programs than lower performing students (Faber et al., 2017).

Moreover, algorithms used in AI applications are often trained on data from specific communities, which are not free from faults and biases, and also continue to change over time (Walker & Baten, 2022). These biases are then included in the algorithm, which can result in the profiling of students in undesirable ways, for example, by consistently rating their performance level lower based on previous performance or by discriminating based on irrelevant background characteristics (Onderwijsraad, 2022).

Data use is a complex process and requires professional development. Technology can support the use of data in schools, but the use of this technology also requires expertise and often professional development. Studies (Keuning & van Geel, 2021; Molenaar & Knoop-van Campen, 2019) have shown that less experienced teachers or teachers without sufficient professional development often benefit less from the advantages that these technologies offer. Moreover, as stated by Keuning and van Geel (2021), technology may also lead to forms of misuse of data, in cases where teachers never question the technology, completely trust the technology and never question the suggestions of the system. The use of these technologies requires a different skills set of teachers, such as interpreting information from the dashboard and understanding how the information in for example adaptive learning systems is calculated (Keuning & van Geel, 2021) and these skills perhaps need to be incorporated into our current definition of data literacy. This is another avenue for further research that I would like to focus on.

Effective education requires a combination of (technology-supported) data use and human decision-making (Schildkamp, 2019) in which a dialogue plays a central role. Data can provide educators with new insights on student outcomes (e.g., learning and achievement, but also health, wellbeing and socio-emotional development). Moreover, technology can be used to analyze and interpret these data, and to provide suggestions for possible courses of action. Educators have their experience, intuition, knowledge, creativity, didactic and pedagogical repertoire, and familiarity with the context. Their strengths include, for example, social interaction, solving problems, and gauging how to react to complex situations (Dellerman et al., 2019, in Onderwijsraad, 2022). Educators need to be aware of what data use (technologies) can and cannot do, and to determine whether and how they will use different forms of data (technologies) (Onderwijsraad, 2022; Walker & Baten, 2022). The combination of the strengths of data (use technologies) and human decision-making (including a dialogue with the data and between the different stakeholders) can lead to higher quality education (Schildkamp, 2019). I intend to investigate further how we can optimize this combination so that school leaders, teachers and students can benefit from all of the potential that data use has to offer. I am looking forward to doing this together with fellow researchers, policymakers and practitioners in a dialogue.

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REFERENCES

Akcaova, G., Baten, D., Poot, G., & Vermaas, K. (2022). *Trendverkenning studiedata. Een exploratie van opkomende waarden & behoeften.* Utrecht: SURF.

Anderson, E. R. (2017). *Accommodating change: Relating fidelity of implementation to program fit in educational reforms. American Educational Research Journal, 54*(6), 1288-1315.

Andrade, H. L. (2019). *A critical review of research on student self-assessment. Frontiers in Education, 4,* 87.

Ansyari, M. F., Groot, W., & De Witte, K. (2022), *A systematic review and meta-analysis of data use professional development interventions. Journal of Professional Capital and Community, 7*(3), 256-289.

Beck, J. S., & Nunnaley, D. (2021). *A continuum of data literacy for teaching. Studies in Educational Evaluation, 69*, 100871.

Bijlsma, H. J., Visscher, A. J., Dobbelaer, M. J., & Veldkamp, B. P. (2019). Does smartphone-assisted student feedback affect teachers' teaching quality? *Technology, Pedagogy and Education, 28*(2), 217-236.

Bolhuis, E., Schildkamp, K., Luyten, H., & Voogt, J. (2017). Het gebruik van data door lerarenopleiders van de pabo [The use of data by teacher trainers]. *Pedagogische studiën, 94*(1), 49-70.

Bolhuis, E. D., Schildkamp, K., & Voogt, J. M. (2016). Improving teacher education in the Netherlands: data team as learning team? *European Journal of Teacher Education, 39*(3), 320-339.

Booher-Jennings, J. (2005). Below the bubble: "Educational triage" and the Texas accountability system. *American Educational Research Journal, 42*(2), 231-268.

Bron, R., van Geel, M. J. M., & Visscher, A. J. (2013). *Opbrengstgericht werken op de PABO. [Data-informed decision making in teacher training colleges]*. Enschede: Universiteit Twente.

Brown, C., & Poortman, C. L. (Eds.). (2018). *Networks for learning: Effective collaboration for teacher, school and system improvement.* Routledge.

Brown, C., Schildkamp, K., & Hubers, M. D. (2017). Combining the best of two worlds: A conceptual proposal for evidence-informed school improvement. *Educational Research, 59*(2), 154-172.

Carless, D., & Chan, K. K. H. (2017). Managing dialogic use of exemplars. *Assessment & Evaluation in Higher Education, 42*(6), 930-941.

Christ, A. A., Capon-Sieber, V., Köhler, C., Klieme, E., & Praetorius, A. K. (2022, September). *The relation of perceived teaching quality to student outcomes: The mediation of learning activities.* Paper presented at the EARLI SIG 18 conference, Freiburg.

Clement, B., Roy, D., Oudeyer, P.-Y., & Lopes, M. (2015). Multi-armed bandits for intelligent tutoring systems. *Journal of Educational Data Mining, 7*(2), 20–48.

Coburn, C. E. (2006). Framing the problem of reading instruction: Using frame analysis to uncover the microprocesses of policy implementation. *American Educational Research Journal, 43*(3), 343-349.

Cohen, D. K. (1990). A revolution in one classroom: The case of Mrs. Oublier. *Educational Evaluation and Policy Analysis, 12*(3), 311-329.

Darling-Hammond, L., Hyler, M. E., Gardner, M. (2017). *Effective teacher professional development.* Palo Alto, CA: Learning Policy Institute.

Datnow, A. (2005). The sustainability of comprehensive school reform models in changing district and state contexts. *Educational Administration Quarterly, 41*(1), 121–153

Datnow, A., Greene, J. C., & Gannon-Slater, N. (2017). Data use for equity: Implications for teaching, leadership, and policy. *Journal of Educational Administration, 55*(4), 354-360.

Datnow, A., & Hubbard, L. (2016). Teacher capacity for and beliefs about data-driven decision making: A literature review of international research. *Journal of Educational Change, 17*(1), 7-28.

Datnow, A., & Park, V. (2018). Opening or closing doors for students? Equity and data use in schools. *Journal of Educational Change, 19*(2), 131-152.

Deunk, M. I., Smale-Jacobse, A. E., de Boer, H., Doolaard, S., & Bosker, R. J. (2018). Effective differentiation practices: A systematic review and meta-analysis of studies on the cognitive effects of differentiation practices in primary education. *Educational Research Review, 24*, 31-54.

de Vries, J. A., Dimosthenous, A., Schildkamp, K., & Visscher, A. J. (2022). The impact on student achievement of an assessment for learning teacher professional development program. *Studies in Educational Evaluation, 74*, 101184.

Ebbeler, J., Poortman, C. L., Schildkamp, K., & Pieters, J. M. (2016). Effects of a data use intervention on educators' use of knowledge and skills. *Studies in Educational Evaluation, 48,* 19-31.

D'Mello, S., Lehman, B., Pekrun, R., & Graesser, A. (2014). Confusion can be beneficial for learning. *Learning and Instruction, 29,* 153-170.

Dutch National AI Coalition. (2022). *Online cursus kunstmatige intelligentie.* Accessed September 29, 2022. https://app.ai-cursus.nl/home

Faber, J. M., Luyten, H., & Visscher, A. J. (2017). The effects of a digital formative assessment tool on mathematics achievement and student motivation: Results of a randomized experiment. *Computers & Education, 106*, 83-96.

Farley-Ripple, E., May, H., Karpyn, A., Tilley, K., & McDonough, K. (2018). Rethinking connections between research and practice in education: A conceptual framework. *Educational Researcher, 47*(4), 235-245.

Fielding, M. (2004). Transformative approaches to student voice: Theoretical underpinnings, recalcitrant realities. *British Educational Research Journal, 30*(2), 295-311.

Fischer, C., Pardos, Z. A., Baker, R. S., Williams, J. J., Smyth, P., Yu, R., ... & Warschauer, M. (2020). Mining big data in education: Affordances and challenges. *Review of Research in Education, 44*(1), 130-160.

Flood, J., & Brown, C. (2018). Does a theory of action approach help teachers engage in evidence-informed self-improvement? *Research for All, 2*(2), 347-358.

Gast, I., Schildkamp, K., & van der Veen, J. T. (2017). Team-based professional development interventions in higher education: A systematic review. *Review of Educational Research, 87*(4), 736-767.

Gebre, E. H. (2018). Young adults' understanding and use of data: Insights for fostering secondary school students' data literacy. *Canadian Journal of Science, Mathematics and Technology Education, 18*(4), 330-341.

Gelderblom, G., Schildkamp, K., Pieters, J., & Ehren, M. (2016). Data-based decision making for instructional improvement in primary education. *International Journal of Educational Research, 80*, 1-14.

Grabarek, J., & Kallemeyn, L. M. (2020). Does teacher data use lead to improved student achievement? A review of the empirical evidence. *Teachers College Record, 122*(12), 1-42.

Gulikers, J., Veugen, M., & Baartman, L. (2021). What are we really aiming for? Identifying concrete student behavior in co-regulatory formative assessment processes in the classroom. *Frontiers in Education, 6*.

Gummer, E. S., & Mandinach, E. B. (2015). Building a conceptual framework for data literacy. *Teachers College Record, 117*(4), 1-22.

Hargreaves, A., & Fink, D. (2012). *Sustainable leadership* (Vol. 6). Wiley.

Hargreaves, A. P., & Shirley, D. L. (Eds.). (2009). *The fourth way: The inspiring future for educational change*. Corwin Press.

Harris, L. R., & Brown, G. T. (2013). Opportunities and obstacles to consider when using peer- and self-assessment to improve student learning: Case studies into teachers' implementation. *Teaching and Teacher Education, 36*, 101-111.

Hebbecker, K., Förster, N., Forthmann, B., & Souvignier, E. (2022). Data-based decision-making in schools: Examining the process and effects of teacher support. *Journal of Educational Psychology.*

Hoogland, I., Schildkamp, K., Van der Kleij, F., Heitink, M., Kippers, W., Veldkamp, B., & Dijkstra, A. M. (2016). Prerequisites for data-based decision making in the classroom: Research evidence and practical illustrations. *Teaching and Teacher Education, 60*, 377-386.

Hubers, M. D., Schildkamp, K., Poortman, C. L., & Pieters, J. M. (2017). The quest for sustained data use: Developing organizational routines. *Teaching and Teacher Education.*

Ingram, D., Louis, K. S., & Schroeder, R. G. (2004). Accountability policies and teacher decision making: Barriers to the use of data to improve practice. *Teachers College Record, 106*(6), 1258-1287.

Jimerson, J. B., Cho, V., & Wayman, J. C. (2016). Student-involved data use: Teacher practices and considerations for professional learning. *Teaching and Teacher Education, 60*, 413-424.

Jülicher, T. (2018). Education 2.0: Learning analytics, educational data mining and co. In T. Hoeren & B. Kolany-Raiser (Eds.), *Big data in context: Legal, social and technological insights* (pp. 47-53). Springer.

Kahneman, D., & Frederick, S. (2005). A model of heuristic judgement. In J. H. Keith & R. G. Morrison (Eds.), Cambridge handbook of thinking and reasoning (pp. 267-293). Cambridge University Press.

Katz, S., & Dack, L. A. (2014). Towards a culture of inquiry for data use in schools: Breaking down professional learning barriers through intentional interruption. *Studies in Educational Evaluation, 42*, 35-40.

Kennedy, B. L., & Datnow, A. (2011). Student involvement and data-driven decision making: Developing a new typology. *Youth & Society, 43*(4), 1246-1271.

Kennisnet (2021). *Handboek digitale geletterdheid.* [Digital literacy manual]. Kennisnet.

Keuning, T., & van Geel, M. (2021). Differentiated teaching with adaptive learning systems and teacher dashboards: the teacher still matters most. *IEEE Transactions on Learning Technologies, 14*(2), 201-210.

Keuning, T., van Geel, M., Visscher, A., & Fox, J. P. (2019). Assessing and validating effects of a data-based decision-making intervention on student growth for mathematics and spelling. *Journal of Educational Measurement, 56*(4), 757-792.

Kippers, W. B., Poortman, C. L., Schildkamp, K., & Visscher, A. J. (2018). Data literacy: What do educators learn and struggle with during a data use intervention? *Studies in Educational Evaluation, 56*, 21-31.

Klenowski, V. (2009). Assessment for learning revisited: An Asia-Pacific perspective. *Assessment in Education: Principles, Policy & Practice, 16*, 263-268.

Lai, M. K., & Schildkamp, K. (2016). In-service teacher professional learning: Use of assessment in data-based decision-making. In G. Brown & L. Harris (Eds.), *Handbook of human and social conditions in assessment* (pp. 77-94). Taylor & Francis.

Lavertu, S. (2014). We all need help: "Big data" and the mismeasure of public administration. *Public Administration Review, 6*(6), 864-872.

Liñán, C. L., & Pérez, J. Á. A. (2015). Educational Data Mining and Learning Analytics: differences, similarities, and time evolution. *International Journal of Educational Technology in Higher Education, 12*(3), 98-112.

Locke, E. A., & Latham, G. P. (2019). The development of goal setting theory: A half century retrospective. *Motivation Science, 5*(2), 93.

Mandinach, E. B., & Gummer, E. S. (2016). What does it mean for teachers to be data literate: Laying out the skills, knowledge, and dispositions. *Teaching and Teacher Education, 60*, 366-376.

Mandinach, E. B., & Jimerson, J. B. (2016). Teachers learning how to use data: A synthesis of the issues and what is known. *Teaching and Teacher Education, 60*, 452-457.

Marsh, J. A. (2012). Interventions promoting educators' use of data: Research insights and gaps. *Teachers College Record, 114*(11), 1-48.

McKenney, S., & Reeves, T. C (2019). *Conducting educational design research.* Routledge.

Ministerie van Onderwijs, Cultuur & Wetenschap. (2017). *Bekwaamheidseisen onderwijspersoneel.*[Required teacher competences]. Retrieved from https://zoek.officielebekendmakingen.nl/stb-2017-148.pdf

Mitra, D. (2004). The significance of students: can increasing" student voice" in schools lead to gains in youth development? *Teachers College Record, 106*(4), 651-688.

Molenaar, I. (2022). Towards hybrid human-AI learning technologies. *European Journal of Education.*

Molenaar, I., & Knoop-van Campen, C. A. N. (2019). How teachers make dashboard information actionable. *IEEE Transactions on Learning Technologies, 12*(3), 317-355.

OECD. (2019). *OECD future of education and skills 2030 Core foundations for 2030.* Retrieved from https://www.oecd.org/education/2030-project/teaching-and-learning/learning/core-foundations/Core_Foundations_for_2030_concept_note.pdf

Onderwijsraad. (2022). *Inzet van intelligentie technologie*. [The use of artifical intelligence].

Panadero, E., Jonsson, A., & Strijbos, J. W. (2016). Scaffolding self-regulated learning through self-assessment and peer assessment: Guidelines for classroom implementation. *In Assessment for learning: Meeting the challenge of implementation* (pp. 311-326). Dordrecht: Springer.

Pardos, Z. A., Tang, S., Davis, D., & Le, C. V. (2017). Enabling real-time adaptivity in MOOCs with a personalized next-step recommendation framework. In C. Thille & J. Reich (Eds.), *Proceedings of the 4th ACM Conference on Learning at Scale* (pp. 23–32).

Penuel, W. R., & Shepard, L. A. (2016). Assessment and teaching. In D. Gitomer & C. Bell (Eds.), *Handbook of research on teaching* (5th ed., pp. 787-850). American Educational Research Association.

Poortman, C. L., Brown, C., & Schildkamp, K. (2022). Professional learning networks: a conceptual model and research opportunities. *Educational Research, 64*(1), 95-112.

Poortman, C. L., & Schildkamp, K. (2016). Solving student achievement problems with a data use intervention for teachers. *Teaching and Teacher Education, 60*, 425-433.

Prenger, R., Poortman, C. L., & Handelzalts, A. (2021). Professional learning networks: From teacher learning to school improvement? *Journal of Educational Change, 22*(1), 13-52.

Prenger, R., & Schildkamp, K. (2018). Data-based decision making for teacher and student learning: a psychological perspective on the role of the teacher. *Educational Psychology, 38*(6), 734-752.

Randel, B., Apthorp, H., Beesley, A. D., Clark, T. F., & Wang, X. (2016). Impacts of professional development in classroom assessment on teacher and student outcomes. *The Journal of Educational Research, 109*(5), 491-502.

Schildkamp, K. (2019). *Data-based decision-making for school improvement: Research insights and gaps. Educational Research, 61*(3), 257-273.
Schildkamp, K. (2022). *Data use for school improvement: achievement, equity and wellbeing.* In W. Böttcher, L. Brockmann, C. Hack, & C. Luig (Eds.). Chancenungleichheit: geplant, organisiert, rechtlich kodifiziert (pp. 15-26). Waxxmann Verlag GmbH.
Schildkamp, K., & Datnow, A. (2022). When data teams struggle: Learning from less successful data use efforts. *Leadership and Policy in Schools, 21*(2), 147-166.
Schildkamp, K., Poortman, C. L., Ebbeler, J., & Pieters, J. M. (2019). How school leaders can build effective data teams: Five building blocks for a new wave of data-informed decision making. *Journal of educational change, 20*(3), 283-325.
Schildkamp, K., Handelzalts, A., Poortman, C. L., Leusink, H., Meerdink, M. A., Smit, M., Ebbeler, J., & Hubers, M. D. (2014). *De datateam® methode: Een concrete aanpak voor onderwijsverbetering* [The data team procedure: a concrete approach to school improvement]. Garant.
Schildkamp, K., Hopster-den Otter, D., Ter Beek, M., Uerz, D., & Horvers, A. (2021). *Building blocks for effective lecturer professional development in higher education aimed at educational innovation with IT. Version 2.0.* Versnellingplan Onderwijsinnovatie met ICT.
Schildkamp, K., & Kuiper, W. (2010). Data-informed curriculum reform: Which data, what purposes, and promoting and hindering factors. *Teaching and Teacher Education, 26*(3), 482-496.
Schildkamp, K., Poortman, C. L., & Handelzalts, A. (2016). Data teams for school improvement. *School Effectiveness and School Improvement, 27*(2), 228-254.
Schildkamp, K., Poortman, C., Luyten, H., & Ebbeler, J. (2017). Factors promoting and hindering data-based decision making in schools. *School Effectiveness and School Improvement, 28*(2), 242-258.
Sipman, G., Thölke, J., Martens, R., & McKenney, S. (2019). The role of intuition in pedagogical tact: Educator views. *British Educational Research Journal, 45*(6), 1186-1202.
Spiele, S., Schildkamp, K., & Janssen, J. (2020). *Do data use professional development interventions for teachers impact student achievement? A meta-analysis.* Paper presented at the 2021 Virtual ICSEI conference.
Staman, L., Timmermans, A. C., & Visscher, A. J. (2017). Effects of a data-based decision making intervention on student achievement. *Studies in Educational Evaluation, 55*, 58-67. https://doi.org/10.1016/j.

stueduc.2017.07.002
Tappel, A. P. M., Poortman, C. L., Schildkamp, K., & Visscher, A. J. (2022). Distinguishing aspects of sustainability. *Journal of Educational Change.*
Tomlinson, C. A. (2015). Differentiation does, in fact, work. *Education Week, 34*(19), 26-32.
Tulowitzki, P. (2016). Educational accountability around the globe. Challenges and possibilities for school leadership. In J. Easly, II & P. Tulowitzki (Eds.), *Educational accountability: International perspectives on challenges and possibilities for school leadership* (pp. 233-238). Routledge.
van den Boom-Muilenburg, E., Poortman, C., de Vries, S., Schildkamp, K., & van Veen, K. (2021). *Leiderschap voor onderwijsontwikkeling: van idee naar duurzame PLG.* [Leadership for school improvement: from first idea to sustainable PLC]. Uitgeverij Phronese.
van der Scheer, E. A., & Visscher, A. J. (2018). Effects of a data-based decision-making intervention for teachers on students' mathematical achievement. *Journal of Teacher Education, 69*(3), 307-320.
van Geel, M., Keuning, T., Visscher, A. J., & Fox, J. P. (2016). Assessing the effects of a school-wide data-based decision-making intervention on student achievement growth in primary schools. *American Educational Research Journal, 53*(2), 360-394.
van Kuijk, M. F. (2014). *Raising the bar for reading comprehension.* University of Groningen.
van Kuijk, M. F., Deunk, M. I., Bosker, R. J., & Ritzema, E. S. (2016). Goals, data use, and instruction: the effect of a teacher professional development program on reading achievement. *School Effectiveness and School Improvement, 27*(2), 135-156.
Valiandes, S. (2015). Evaluating the impact of differentiated instruction on literacy and reading in mixed ability classrooms: Quality and equity dimensions of education effectiveness. *Studies in Educational Evaluation, 45*, 17-26.
Vanlommel, K., & Schildkamp, K. (2019). How do teachers make sense of data in the context of high-stakes decision making? *American Educational Research Journal, 56*(3), 792-821.

Vanlommel, K., Van Gasse, R., Vanhoof, J., & Van Petegem, P. (2017). *Teachers' decision-making: Data based or intuition driven? International Journal of Educational Research, 83,* 75-83.

van Veen, K., Zwart, R., & Meirink, J. (2012). What makes teacher professional development effective? A literature review. In M. Kooy & K. van Veen (Eds.), *Teacher learning that matters* (pp. 23-41). Taylor & Francis.

Veldkamp, B.P, Schildkamp, K., Keijsers, M., Visscher, A.J., & De Jong, A.J.M. (2017). *Verkenning data-gedreven onderwijsonderzoek in Nederland* [Exploration of big data in education]. Enschede: Universiteit Twente.

Veldkamp, B., Schildkamp, K. Keijsers, M., Visscher, A. & de Jong, T. (2021). *Big data analytics in education: big challenges and big opportunities.* In: A. Wilmers & S. Jornitz (Eds). International perspectives on school settings, education policy and digital strategies. A transatlantic discourse in education research (pp. 266-282). Leverkusen (Germany): Barbara Budrich Publishers.

Visscher, A. J. (2021). On the value of data-based decision making in education: The evidence from six intervention studies. *Studies in Educational Evaluation, 69*, 100899.

Walker, J. & Baten, D. (2022). *Promises of AI in education.* SURF.

Weick, K. E. 1995. *Sensemaking in organizations.* Sage.

Weiss, C. H. (1998). Have we learned anything new about the use of evaluation? *American Journal of Evaluation, 19*(1), 21-33.

Wiliam, D., & Leahy, S. (2015). *Embedding formative assessment: Practical techniques for K-12 classrooms.* Learning Sciences International.

Wiltsey-Stirrnam, S., et al. (2012). The sustainability of new programs and innovations: A review of the empirical literature and recommendations for future research. *Implementation Science, 7*(17), 1–19.

Wolff, A., Gooch, D., Montaner, J. J. C., Rashid, U., & Kortuem, G. (2016). Creating an understanding of data literacy for a data-driven society. *The Journal of Community Informatics, 12*(3).

Wolterinck, C., Poortman, C., Schildkamp, K., & Visscher, A. (2022). Assessment for Learning: developing the required teacher competencies. *European Journal of Teacher Education*, 1-19.

Yonezawa, S., & Jones, M. (2007). Student co-researchers: How principals can recruit, train, and enlist the help of students to examine what works and does not work in their schools. *NASSP Bulletin, 91*(4), 322-342.

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