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Learning Analytics in Schools: Is Digital Data Use Influenced by Teacher-Level or School-Level Factors?

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Abstract

Digital transformation in schools involves the use of digital data to inform teachers' pedagogical decisions. Previous research indicates that a deeper understanding of the factors influencing teacher utilization of learning analytics and a comprehensive school context analysis is required. In this article, we conducted a survey study with N = 2,247 teachers in 112 upper secondary schools in Switzerland to examine teacher characteristics and school-related factors that impact teacher use of digital data for pedagogical purposes. The results show that teacher characteristics including their positive beliefs about technologies, competency with digital data, and availability of data technologies significantly predict their digital data use, with differences identified between subject matter teachers and schools. School-related factors about digitalization, such as formal and informal collaboration between colleagues and support from school principals, indirectly influence teachers' digital data use, mediated by teacher characteristics. Based on these results, personalized support can be formulated for teacher utilization of learning analytics according to their characteristics and the supportive school environment.

Notes for Practice

- Large-scale studies in learning analytics in schools are scarce.
- This large-scale survey study examined teacher-level and school-level factors related to the pedagogical use of digital data by teachers in various upper secondary schools.
- Teacher use of digital data is influenced not solely by their own characteristics or by school factors but rather by a combination of both.
- Personalized support, tailored to teacher characteristics and addressing subject-specific differences, could enhance digital data use practices in schools.

Keywords: Schools, teachers, learning analytics, digital data use, digital transformation

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1. Introduction

School environments currently offer new spaces for learning through digital tools and devices such as computers, tablets, and mobiles. As schools increasingly use digital technologies more comprehensively, opportunities for analyzing and utilizing digital data emerge. Digital data are typically generated during classroom and home-based learning activities, and these digital traces can be used by teachers for instructional purposes and curriculum development (Monroy et al., 2014). The use of digital data in education has been studied in the fields of learning analytics and educational data mining, primarily in higher education (Lang et al., 2017). In the past few years, research has also focused on the use of digitally generated data in K–12 schooling (Bond et al., 2023; Hung et al., 2019; Jarke & Breiter, 2019; Kovanović et al., 2021; Selwyn, 2023).

Existing evidence from learning analytics in higher education is challenging to apply to schools due to contextual factors such as the school type, the level of support provided by teachers, the different modes of instruction, and the teaching subjects (Bond et al., 2023). Moreover, there has been an increase in the adoption of digital technologies and new classroom-focused

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technologies in primary and secondary education following the COVID-19 pandemic (Kovanović et al., 2021). Consequently, teachers and students are increasingly engaging with digital data. However, the integration of digital data and learning analytics tools in schools has been slow, influenced by factors such as limited understanding of the benefits of learning analytics, ethical concerns, and privacy issues (Hirsto et al., 2022; Krumm et al., 2018). Previous research indicates a need for a deeper understanding of teacher utilization of learning analytics in schools and the factors that drive their use (Kovanović et al., 2021; Monroy et al., 2014). Additionally, there is a call for more theory-grounded studies to address theoretical conceptualization issues in learning analytics research (Bond et al., 2023).

This study aims to identify factors influencing teacher use of digital data and learning analytics tools in schools based on existing theoretical frameworks. A large-scale survey study was conducted among upper secondary school teachers in Switzerland. The contributions of the study are relevant for the uptake of learning analytics in schools and issues of teacher professional development on digital educational data.

2. Learning Analytics in Schools

Learning analytics involves using data generated in educational contexts to better understand and support learning processes (Long & Siemens, 2011). In K–12 education, its adoption remains limited, requiring a focus on teacher engagement and school contexts (Kovanović et al., 2021; de Sousa et al., 2021). The use of data to support decision-making in schools has a long tradition (Hase & Kuhl, 2024; Schildkamp & Kuiper, 2010). Currently, the everyday use of educational software in schools, such as learning management systems, automated personalized systems, and digital assessments generates "trace data" that are configured as feedback and analytics to inform teachers and students (Selwyn, 2023; Martens et al., 2024; Jarke & Breiter, 2019). School digital data play a crucial role in this digital transformation, as these data platforms include data tracking, sensing, and analytics technologies (Jarke & Breiter, 2019), necessitating the further development of teacher skills for instructional practices (Celik et al., 2022; Howard et al., 2022; Mandinach & Abrams, 2022). In particular, the collection of digital data for pedagogical purposes (e.g., for improving teaching and learning), especially within the classroom, requires teachers to process digital data (e.g., in the form of teacher dashboards [van Leeuwen et al., 2021]) and design pedagogical actions accordingly (Hirsto et al., 2022; Krein & Schiefner-Rohs, 2021). This digital transformation in school data–related practices (Jarke & Breiter, 2019; Selwyn, 2023) raises issues about current digital data use, teacher competency (Krein & Schiefner-Rohs, 2021), and teacher data literacy (Lee et al., 2024; Mandinach & Abrams, 2022), which is defined as "the ability to transform information into actionable instructional knowledge and practices by collecting, analyzing, and interpreting all types of data (assessment, school climate, behavioural, snapshot, etc.) to help determine instructional steps" (Mandinach & Gummer, 2016, p. 367). Teacher ability to effectively use digital data is therefore critical, as it both supports data-informed instructional practices and influences the broader digital transformation in schools.

A literature review on learning analytics in high schools found a lack of studies that explore the school context and the actual needs in using digital data and learning analytics in schools (de Sousa et al., 2021). School systems are highly heterogeneous in their culture, practices, and attitudes toward technology use. A global exploration of learning analytics in schools from different countries (Finland, China, South Africa, Uruguay, and the USA) shows that data utilization is more complex and heterogenous than data collection (Aguerrebere et al., 2022). Among the pedagogical perspectives in schools, research has often focused on gamification, problem-solving, and collaborative learning (Hirsto et al., 2022). For instance, studies in schools explored the use of Kinect games (motion controller games) and multimodal data but also computational thinking, robotics, and learning analytics (Hirsto et al., 2022). Additionally, various studies have been conducted with teacher dashboards in mathematics (Molenaar & Knoop-Van Campen, 2019), inquiry-based learning (Sergis et al., 2019), computer-supported collaborative learning (van Leeuwen et al., 2019), formative assessment, and feedback (Karademir et al., 2024).

Research on learning analytics in schools focuses either on the use of analytics tools (e.g., adaptive learning systems) by educational stakeholders such as teachers and students or on analytics methods for conducting research (e.g., multimodal data, advanced analytics techniques; Hirsto et al., 2022). Regarding the involvement of stakeholders, an increasing number of studies show the importance of co-designing learning analytics tools with teachers and better understanding teacher needs. For example, Karademir et al. (2024) conducted interviews with secondary school teachers to design a formative assessment dashboard and found that the lack of teacher time was a key barrier. Moreover, Wiley et al. (2024) show that involving teachers with different characteristics and backgrounds in co-design reinforces the expected outcomes of teacher dashboards in K–12 contexts. In summary, teacher perceptions of the use of digital data in schools could also influence the integration of learning analytics in classrooms. However, most studies had small samples of teachers, and few studies were conducted on a larger scale by incorporating school-related factors.

3. Teacher Characteristics and School-Related Factors

A recent literature review combined research on digital learning platforms and how teachers use digital data for instructional purposes in schools (Hase & Kuhl, 2024). The authors concluded that few studies were identified, and most were explorative in nature. A lack of large-scale studies evaluating digital learning platforms and digital data use by teachers was found. Among the digital platforms used in schools were learning management systems and intelligent tutoring systems, with digital data use employed by teachers for individualization and differentiation of instruction. Although limited studies exist, the factors influencing teacher use of digital data from digital learning platforms remain underexplored.

Different theoretical frameworks have been used to evaluate teacher-related factors regarding the use of digital data or learning analytics in schools on a large scale. The frameworks include the technology acceptance model (TAM; Davis, 1989), the theory of planned behaviour (TPB; Ajzen, 1991), the will-skill-tool model (Knezek & Christensen, 2016), and a process model for the use of teacher dashboards (Verbert et al., 2013). Based on TPB, factors such as teacher autonomy to make instructional changes based on data, beliefs about data, and teacher competence with data have been found to predict the use of data or learning analytics in schools (Hase et al., 2022; Prenger & Schildkamp, 2018; Schildkamp, 2019). Based on the TAM model, teachers generally perceive learning analytics positively, but they are more skeptical about their readiness for actual use in schools (Mavroudi et al., 2021). The will-skill-tool model has also been shown to explain a high degree of variance in use of digital data by schoolteachers, with teacher competency in digital data identified as the main predictor (Michos et al., 2023). This model's assumption is that teachers' positive beliefs toward technology use in class (will), their technical skills (skill), and the quality of the school digital infrastructure (tool) significantly and positively predict technology integration (Knezek & Christensen, 2016), which in this case is relevant to learning analytics technologies. Finally, Verbert's process model has been applied in various studies about teacher dashboards in school classrooms, suggesting that both general characteristics (e.g., technological skills, age, teaching years) and complex characteristics (e.g., data literacy, pedagogical routines, and pedagogical knowledge) influence teacher dashboard use (van Leeuwen et al., 2021).

In this article, the will-skill-tool model (Knezek & Christensen, 2016) was chosen as the conceptual framework because it provides a comprehensive perspective on the interplay between individual and contextual factors in technology integration. The model captures three critical dimensions: 1) teacher motivation and beliefs (will), 2) their competencies and skills (skill), and 3) the availability and accessibility of digital tools (tool). These dimensions align closely with the factors influencing teacher use of digital data in pedagogical practices, as identified in prior research on technology adoption in schools (Petko et al., 2018). Compared to other models, such as the technological pedagogical content knowledge (TPACK) framework (Mishra & Koehler, 2006), the will-skill-tool model offers a more pragmatic focus on teacher-level characteristics and their interaction with contextual enablers, making it particularly suitable for examining digital data use in schools (Michos et al., 2023).

However, both the internal (e.g., teacher characteristics) but also external factors (e.g., school support) have been shown to influence the use of digital platforms and data by teachers. Large-scale studies have demonstrated that school-related factors such as overall and technological support, informal and formal collaboration, the importance of information and communication technology (ICT) within the school, and school principal support positively predict the use of educational technologies (Fang et al., 2024; Inan & Lowther, 2010; Petko et al., 2018). School leaders, in particular, can create a positive atmosphere regarding the use of digital technologies in teaching by strengthening teacher collaboration and sharing best practices (Håkansson Lindqvist, 2019). Moreover, the attitudes and behaviours of school leaders significantly impact teacher engagement in data use, influenced by the school system, organization, and team/individual factors (Schildkamp, 2019). Collaboration among teachers in data use can enhance decision-making processes by making them more transparent and reproducible (Vanlommel & Schildkamp, 2019). Additionally, the relationship between teacher agency, school structure, and culture in data use efforts requires further exploration (Lockton et al., 2020).

Although school-related factors have been widely studied in the context of technology integration and teacher data use, large-scale studies evaluating both teacher characteristics and school-related factors in the use of data generated by digital platforms are still lacking (Hase & Kuhl, 2024). In this article, the use of digital data in schools is viewed as a prerequisite for the development and application of learning analytics. Therefore, this study aims to contribute to the field of learning analytics by examining whether this prerequisite — the use of digital data — is established in K–12 school settings. Previous research has identified teacher characteristics as influential in the adoption of learning analytics in schools. However limited research explores how teachers use digital data in relation to contextual factors, such as teaching subjects and school variations. Additionally, little is known about the range of school-related factors that influence teacher use of digital data when integrating digital technologies into classroom teaching.

This study seeks to address the following research questions considering both teacher and school-related factors:

RQ1: To what extent do teacher characteristics, such as data literacy, positive beliefs toward technologies, and availability of data technologies influence their use of digital data, considering the variance between schools?

To investigate this research question, we initially evaluated the current situation of teachers regarding the use of digital data for pedagogical purposes in schools. We then analyzed how teacher factors related to the will-skill-tool model and other teacher characteristics — such as their teaching subjects, number of years in the profession, age, and gender — influence their engagement with digital data. Based on our previous study (Michos et al., 2023), we expect that factors related to the will-skill-tool model will positively predict the use of digital data by teachers, considering the variance between schools. In our previous study, we also evaluated the digital platforms used, such as learning management systems, and cloud-based platforms for collaboration, and found that about 84% of teachers had access to digital platforms providing learning analytics. However, differences between teaching subjects have not been evaluated in previous studies on learning analytics in schools. Therefore, we also explore differences between subject matter teachers.

RQ2: To what extent do school factors influence the use of digital data by teachers?

We explore different school factors such as the importance of ICT in the school, formal and informal collaboration around the use of digital technologies, and school principal support. We expect that school factors will influence the use of digital data by teachers.

RQ3: To what extent do school factors influence the use of digital data by teachers considering teacher characteristics as mediators?

We expect that teacher characteristics will mediate school factors related to the will-skill-tool model, based on previous findings on technology integration in schools and teacher data use. Our conceptual model posits that school-related factors, such as leadership support and collegial collaboration, influence teacher use of digital data indirectly through teacher-level characteristics. Specifically, these school factors create an environment that fosters teacher motivation (will), enhances their data-related competencies (skill), and ensures access to digital tools (tool). This mediation is grounded in previous findings, which suggest that teacher-level factors play a crucial intermediary role in translating school-level conditions into actual technology use (Fang et al., 2024; Inan & Lowther, 2010; Michos et al., 2023; Petko et al., 2018).

4. Methods

4.1. Context and Sample

An online survey was conducted between May 1 and August 1, 2022. Teachers in all cantons of Switzerland who teach in the second and third years of upper secondary schools were invited to participate. Of the 497 schools contacted, 124 took part in the study. The response rate of the schools was therefore 24.9%. After data cleaning, the sample includes N = 2,247 teachers (9.5% of the whole sample of teachers) from 112 schools. One case was excluded from the final analysis because one teacher was the only responder from a school. Of the participants, 50.5% were male, 47.3% were female, and 2.2% responded as "other" for their gender. Teachers had an average of 15.7 years of teaching experience (SD = 9.6) and were 46.1 years old (SD = 10.1). Of the responders, 41.8% were teaching in general education schools, 40.7% in vocational schools, and 17.5% in schools offering both general and vocational education. Regarding teaching subjects, 37.4% of teachers taught subjects related to languages, arts, and humanities; 20.0% taught STEM subjects; 15% taught vocational subjects; 5.3% taught sports, music, and other subjects; and 22.2% taught at least two subjects from the previously mentioned categories (mixed). Additionally, 79.4% of responders were working in the German-speaking part of Switzerland, 9.5% in the francophone region, and 11.3% in the Italian-speaking region.

4.2. Instruments

4.2.1. Teacher Characteristics

The WST model was used as a theoretical framework to understand teacher-related factors that influence the use of digital data by teachers in schools. Teachers' positive beliefs about technologies in general (will) were evaluated using a scale (Cronbach's alpha =.895) including four items from Petko (2012):

- "Through the use of digital technologies, I can improve the quality of my teaching"
- "The performance of learners can be increased when using digital technologies"
- "When learners work with digital technologies, they can improve learning and their working strategies"
- "Through the use of digital technologies, the work efficiency of learners can be increased"

The four items included a 5-point Likert scale ranging from "Strongly disagree" to "Strongly agree."

The use of digital data by teachers was measured with items from the Teacher Data Use Survey (Wayman et al., 2016) that evaluates teachers' pedagogical actions based on data to improve instruction in school contexts. The items were adapted to the context of this study, focusing on digital platforms, and treated as single items. One item evaluated whether teachers have access to available technologies for the analysis of digital student data in their schools, which represents the tool-component in the WST model: "I have adequate technology to examine digital student data." Another item related to teacher data literacy regarding the use of digital student data, which constitutes the skill-component in the WST model: "I know how to improve my teaching and student learning by analyzing digital student data." Finally, one item evaluated the pedagogical use of digital student data by teachers, which represents the outcome variable of effective digital data use: "I use digital student data to plan and adjust my teaching." These three items also used a 5-point Likert scale ranging from "Strongly disagree" to "Strongly agree." In addition, four demographic items were included regarding teacher' characteristics: years of teaching experience, gender, age, and teaching subjects.

4.2.2. School-Related Factors

School-related factors included items in a 5-point Likert scale ranging from "Strongly disagree" to "Strongly agree," addressing the importance of ICT in the school, leader support, goal clarity in the integration of digital technologies, and informal and formal collaboration between colleagues regarding the use of digital technologies. These items were based on existing studies (Fang et al., 2024; Inan & Lowther, 2010; Petko et al., 2018; Prasse, 2012). Table 1 presents these items.

Table 1. School-Related Factors and Items in the Questionnaire

ICT importance (Cronbach's alpha = .791)	–The topic of digitalization is very important at our school. –In our school, there is a lot of emphasis on the training regarding digital media. –Particular commitment to the use of digital media in teaching is highly valued among colleagues.
Leader support (Cronbach's alpha = .777)	–The school management clearly supports the integration of digital media in schools. –Colleagues with new ideas for using digital media are actively supported by the school management. –The school management is well informed about ICT use among teachers.
Goal clarity (Cronbach's alpha = .761)	–The school's goals for the use of digital media are clear to me. –The pedagogical and didactic concepts among the teaching staff regarding the use of digital media can be well aligned to a common denominator. –The colleagues at my school are committed to common goals for the use of digital media.
Informal collaboration (Cronbach's alpha = .756)	–Teachers work very closely in the development and implementation of digitally supported teaching units (e.g., joint projects, coordination of teaching content). –We discuss our experiences regarding the possible uses of digital media very intensively. –The teaching staff is also well informed about the ICT usage of colleagues from other schools.
Formal collaboration (Cronbach's alpha = .802)	–It often happens at our school that colleagues present something on the topic of using digital media in teaching (e.g., in conferences, through notices). –It often happens at our school that internal informational events on the topic of using digital media in teaching take place. –It often happens at our school that experiences with digital media are exchanged with external partners/schools (e.g., invitations to lectures, excursions).

4.3. Data Analysis

We used descriptive statistics to report all variables related to teachers' digital data use and characteristics, including their teaching subjects. To account for the number of participants per school, school type, and language region, we used weighted data (Meinck, 2015). To evaluate the first research question regarding the relationship between teacher characteristics related to the WST model, their teaching subjects, and the use of digital data by teachers, we used a multilevel regression model with two levels (teachers and schools). This approach was employed because teachers were nested within schools, which could have influenced their use of digital data. After checking the statistical prerequisites, we used a multilevel model with a random intercept and centred the predictors based on group means (Enders & Tofighi, 2007; Field, 2013; Peugh, 2010). For inferential statistics, we used unweighted data to avoid distorted results in regression analysis (see Gelman, 2007). This approach ensures that the relationships between variables are accurately identified and are not influenced by sampling weights.

The predictor variables were positive beliefs about technology use (will), teacher data literacy (skill), availability of data technologies (tool), teacher characteristics (gender, age, teaching years), and their teaching subjects. We initially estimated an unconditional model (null model) to understand whether there were differences in digital data use for teaching at the teacher and school levels. We then created a model with all the predictor variables. To identify differences between different teaching subjects, we performed post hoc tests with Bonferroni correction. The analysis was carried out using Jamovi (version 2.3).

To evaluate the second and third research question regarding school-related factors (RQ2) and their mediation by teacher characteristics (RQ3), we used a structural equation model (SEM). SEM combines evaluating a measurement model fit with a regression (Ullman & Bentler, 2012). In our dataset, this allows us to analyze the influence of context (school factors) and teacher characteristics based on the will-skill-tool theoretical framework. This analytical method was chosen because we analyzed both teacher and school factors and their mediation (RQ3). Since our sample did not have enough clusters for a latent multilevel SEM (McNeish, 2017), we performed a latent one-level SEM with cluster robust standard errors to account for the multilevel structure of the data (see Oberski, 2014; Stapleton et al., 2016). The analysis used the package lavaan (0.6–7) in R (4.1.2.). We employed the conceptual model shown in Figure 1 to understand the relationships between the variables. We conducted SEM with school-related factors as predictors and digital data use by teachers as the outcome variable. Teacher beliefs (will), teacher data literacy (skill), and availability of data technologies (tool) were considered as mediators. In a first step, each school-level factor (e.g., leader support, goal clarity) was measured using multiple items, and these items were combined to form single latent factors for each construct. In a second step, these latent constructs loaded on an overarching latent factor called "school-related factors." This second order factor analysis was necessary since we could not investigate the influence of the single constructs on the mediators and the outcome variable due to the sample size.

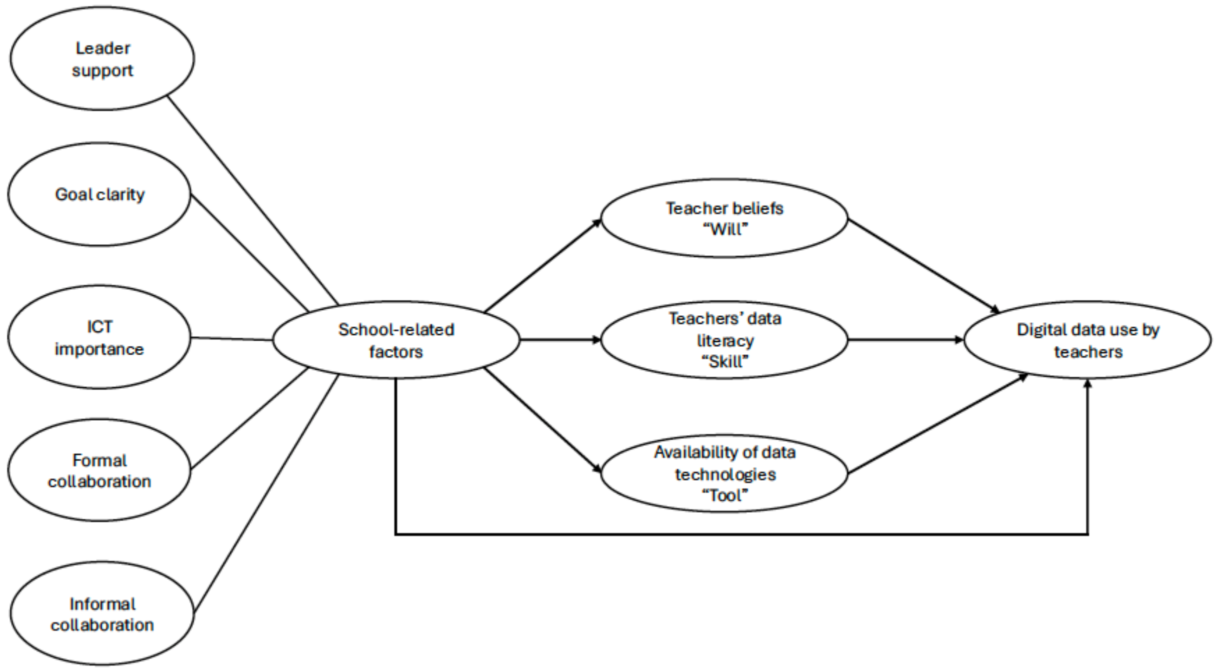

Figure 1. Conceptual model of school-related factors and mediation of the will-skill-tool model as a teacher characteristic in the use of digital data by teachers.

5. Results

5.1. Descriptive Statistics

The three items regarding teachers' digital data use (Table 2) indicate that almost 50% of teachers agreed on having access to technologies that provide digital student data. However, 47% of teachers disagreed on knowing how to improve their teaching and student learning with digital data. Similarly, almost 50% of teachers disagreed with using digital student data from available platforms to plan and adjust their teaching.

Table 2. Proportion of Teachers and their Responses to the Three Items of Teachers' Digital Data Use (Weighted Percentages)

Teacher Data Use Items	1. Strongly disagree	2.	3.	4.	5. Strongly agree
	N (%)	N (%)	N (%)	N (%)	N (%)
Availability of data technologies: I have adequate technology to examine digital student data.	271 (12.1)	381 (17)	481 (21.4)	593 (26.4)	520 (23.1)
Teacher data literacy: I know how to improve my teaching and student learning by analyzing digital student data.	580 (25.8)	541 (24.1)	548 (24.4)	389 (17.3)	188 (8.4)
Digital data use by teachers: I use digital student data to plan and adjust my teaching.	555 (24.7)	501 (22.3)	474 (21.1)	364 (16.2)	353 (15.7)

This tendency of teachers to report a higher availability of data technologies in schools but medium score in their skill or use of digital data is also presented in Table 3. Regarding the use of digital technologies for teaching and learning, teachers generally had positive beliefs.

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Table 3. Descriptive Statistics on Teachers' Questionnaire Items (Weighted Data) N = 2,247

Variables	M (SD)
Digital data use by teachers	2.76 (1.39)
Teachers' positive beliefs regarding digital technologies (will)	3.38 (0.94)
Teachers' data literacy (skill)	2.58 (1.26)
Availability of data technologies (tool)	3.32 (1.32)

Descriptive statistics show that teachers in languages, arts, humanities, and social sciences tend to report higher skill and use of digital data to inform their teaching compared to teachers in STEM subjects. However, the teachers who report the highest levels in all variables are those who teach vocational education subjects or multiple subjects in general or vocational schools based on the categories shown in Table 4.

Table 4. Descriptive Statistics on Teachers' Digital Data Use Based on their Teaching Subjects (Weighted Data)

Variables	Languages, arts, humanities, social sciences	STEM	Vocational subjects	Other	Multiple subjects
	N = 714	N = 404	N = 499	N = 88	N = 537
Digital data use by teachers	2.68 (1.36)	2.45 (1.68)	2.99 (1.53)	2.73 (1.40)	2.89 (1.32)
Teacher data literacy	2.56 (1.25)	2.42 (1.25)	2.63 (1.34)	2.56 (1.16)	2.69 (1.23)
Availability of data technologies	3.23 (1.37)	3.24 (1.36)	3.40 (1.29)	3.02 (1.31)	3.47 (1.24)
Positive beliefs regarding digital technologies	3.35 (0.03)	3.18 (0.98)	3.51 (1.02)	3.49 (0.99)	3.45 (0.86)

5.2. Inferential Statistics: Teacher Characteristics

The multilevel regression model (Table 5) shows that 11% of the variance in digital data use by teachers (intraclass correlation-ICC) is attributed to differences between schools (null model), and the between-schools variance differed significantly from zero. Model 1, which included all the predictor variables, had a better fit compared to the null model and explained 52% of the variance in the use of digital data by teachers. The variables that mostly influence the use of digital data by teachers were all related to the WST model, namely positive beliefs toward digital technologies (will; $B = 0.13$, $p < 0.001$), teacher competency with digital data (skill; $B = 0.55$, $p < 0.001$), and availability of data technologies (tool; $B = 0.40$, $p < 0.001$), as well as the teaching subjects. Other teacher characteristics, such as age and gender, did not significantly affect the use of digital data, but years of teaching experience had a minor negative impact ($B = –0.09$, $p < 0.001$).

Table 5. Multilevel Regression Model for the Predictors of Digital Data Use Based on Teacher Characteristics and the WST Model

	Digital data use by teachers	
	Null model	Model 1
Fixed effects intercept	2.78 (0.05)	2.78 (0.06)
Availability of data technologies (tool)		0.40 (0.02)***
Teacher data literacy (skill)		0.55 (0.02)***
Teachers' positive beliefs regarding digital technologies (will)		0.13 (0.02)***
Teaching years		–0.09 (0.03)**
Age		0.04 (0.03)
Female–Male		0.04 (0.04)
Other–Male		–0.16 (0.15)
STEM–languages, arts, and humanities		–0.27 (0.06)***
Vocational–languages, arts, and humanities		0.22 (0.08)**
Other–languages, arts, and humanities		0.06 (0.10)
Multiple subjects–languages, arts, and humanities		0.03 (0.06)
Random effect intercept variance	0.20 (0.45)	0.23 (0.48)
ICC	0.11	0.20
Deviance	7,665.85	6,252.02
AIC	7,671.85	6,280.05
BIC	7,688.99	6,359.92
R-squared marginal	–	0.40
R-squared conditional	0.11	0.52

Note. For fixed effects, the estimate and standard error in brackets are reported. For random intercepts, the variance and standard deviation in brackets are reported. For Model 1: *N* = 2,225 (22 cases were excluded because age and/or teaching years and/or subject category were coded as missing), Clusters = 112. * *p* <.05, ** *p* <.01, *** *p* <.001.

Further differences between the teaching subjects were examined (Table 6). Post hoc analysis with Bonferroni correction showed a significant difference in digital data use between teachers who teach languages, arts, and humanities subjects and those who teach STEM subjects (z = 4.49, p < =.001). Moreover, significant differences were found between teachers in vocational schools and teachers who teach languages, arts, and humanities (z = 2.82, p =.048) or STEM subjects (z =5.57, p < =.001).

Table 6. Post Hoc Comparisons Between Different Teaching Subjects

Comparison						
Subject categories		Difference	SE	t	df	$p_{bonferroni}$
Languages, arts, and humanities	–Multiple subjects	–0.03	0.06	–0.50	2,196	1.00
Languages, arts, and humanities	–STEM	0.27	0.06	4.49	2,186	< .001
Languages, arts, and humanities	–Other	–0.06	0.10	–0.61	2,177	1.00
Languages, arts, and humanities	–Vocational	–0.22	0.08	–2.83	2,064	0.048
STEM	–Multiple subjects	–0.29	0.07	–4.43	2,216	< .001
STEM	–Other	–0.32	0.10	–3.17	2,180	0.015
STEM	–Vocational	–0.48	0.09	–5.58	2,036	< .001
Other	–Multiple subjects	0.03	0.10	0.30	2,185	1.000
Vocational	–Multiple subjects	0.19	0.08	2.39	2,188	0.172
Vocational	–Other	0.16	0.11	1.38	2,234	1.000

5.3. Inferential Statistics: School- and Teacher-Related Factors

Since differences between schools were identified in the previous analysis, we further analyzed school-related factors that affect digital data use mediated by teacher characteristics. After 10 modifications allowing for covariances between items, the mediation model has a good model fit (Chi^2 (187) = 1,209.376; p <.001; TLI = 0.951; CFI = 0.960; RMSEA = 0.048; SRMR = 0.043). These modifications involved allowing covariances between specific item pairs that showed residual correlations, which helped address potential misspecifications in the model. The results of the SEM model are shown in Figure 2. The R^2 was 0.5, indicating that 50% of the variance in digital data use could be attributed to school-related factors mediated by teacher characteristics (will-skill-tool).

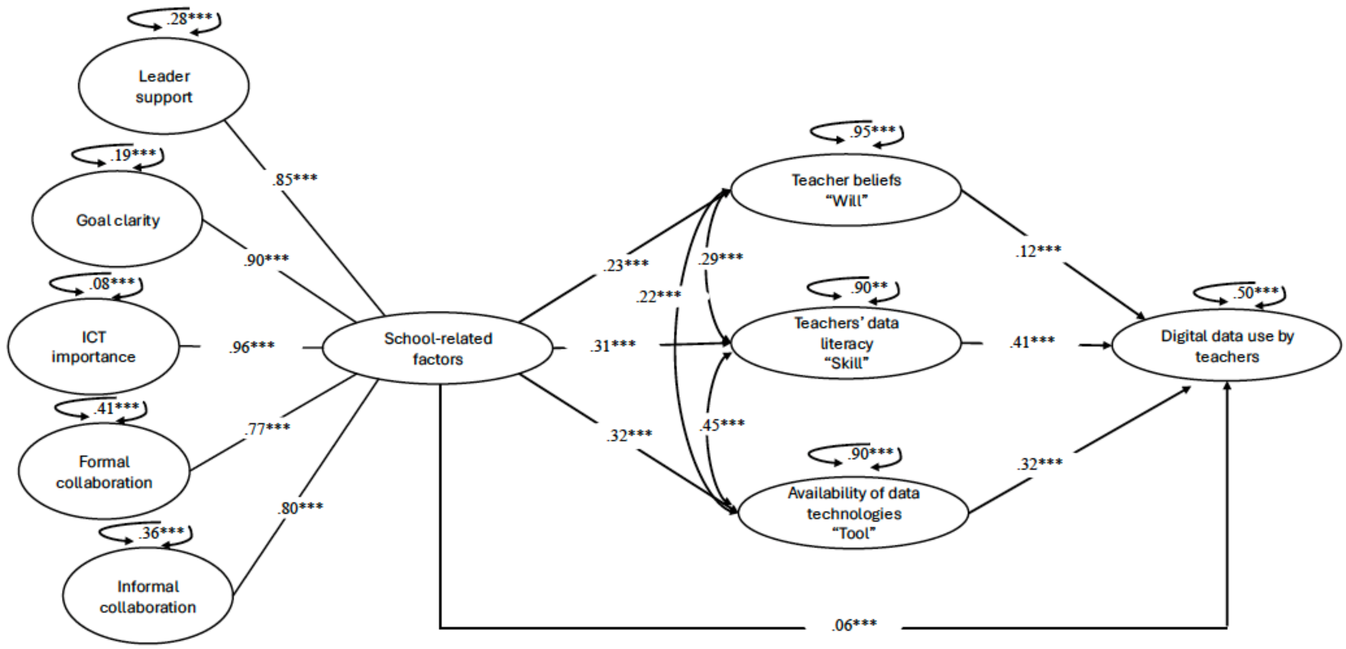

Figure 2. Structural equation model (SEM) showing school-related factors mediated by teacher characteristics.

Note. ***p <.001. All standardized path coefficients and covariances between latent variables and the variances explained by the endogenous variables are displayed. Factor loadings of items are not displayed.

The SEM model indicates that school-related factors had a tiny direct impact on digital data use by teachers. Among the different school-related factors, goal clarity and ICT importance were more crucial in the model (based on standardized path coefficients). School-related factors significantly impacted all teacher characteristics related to the will-skill-tool model, namely positive beliefs about digital technologies, competency in using digital data, and availability of data technologies. As Figure 2 indicates, school-related factors influence more teacher skill with data and the availability of data technologies. In addition, all these teacher characteristics showed a positive significant impact on digital data use by teachers, with teacher data literacy having the strongest effect (as shown by comparing standardized path coefficients). As Table 7 shows, all the indirect effects were significant, demonstrating that school-related factors indirectly affect digital data use by teachers and are mediated by teacher characteristics.

Table 7. Standardized Indirect and Total Effects

	Estimate	SE	p	CI lower	Ci upper
Indirect effect school–will	.03	.01	.000	.02	.04
Indirect effect school–skill	.13	.02	.000	.10	.16
Indirect effect school–tool	.10	.01	.000	.08	.13
Total	.31	.03	.000	.25	.38

6. Discussion

The ongoing digital transformation in schools involves not only the digitalization of teaching and learning practices but also the increased use of data to inform instruction and improve schools (Schildkamp, 2019; Schildkamp & Kuiper, 2010).

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Datafication creates new opportunities as digital platforms provide a variety of digital data that teachers can use to enhance their teaching (Jarke & Breiter, 2019). However, the integration of digital data and learning analytics into everyday teaching requires a deeper understanding of the factors influencing teacher readiness and capacity to adopt these technologies. This includes considering teacher competencies, school environments, and the availability of digital platforms (Hase & Kuhl, 2024; Hirsto et al., 2022; de Sousa et al., 2021).

In this article, building upon previous large-scale studies that have explored teacher perceptions of digital data or learning analytics in schools, we investigated the influence of both teacher characteristics and school-related factors on the utilization of digital data by teachers across Switzerland. Our first research question (RQ1) considered teacher characteristics and differences between schools. The results show that about 50% of teachers agree on having access to data technologies in their schools. However 47% disagree that they know how to improve teaching and learning with the use of digital data, and almost 50% disagree that they use digital data to plan and adjust their teaching. This result reveals that the technologies are available and there are opportunities to use digital student data for teaching, but teachers are hesitant about their skill level and their actual use of digital student data. This result aligns with previous research conducted in schools that found teachers perceive the usefulness of learning analytics positively, but they are skeptical about their readiness and actual use in their practice (Mavroudi et al., 2021). This result might show the need for further practical applications, training, and experiences of digital data use by teachers, such as learning analytics tools (e.g., teacher dashboards) and data-driven technologies in the classroom. In this study, we evaluate how teachers use data generated by digital platforms. While learning analytics involves not just data use but also interpreting and applying this data to enhance teaching and learning, our focus is on whether the conditions for adopting learning analytics are established in K–12 schools.

Based on our evaluation of teacher-related factors, one main finding of our study is that teacher characteristics related to the will-skill-tool theoretical framework are relevant to predicting the use of digital data, with teacher competency being the strongest predictor. This result also confirms our previous study, conducted with a smaller sample in the German-speaking area of Switzerland (Michos et al., 2023). However, in the current study, conducted across all of Switzerland, we also found differences between contextual factors, namely teachers who teach different subjects and at different types of schools. Vocational teachers reported higher use of digital data to inform their teaching, followed by teachers in languages, arts, and humanities, and then teachers in STEM subjects. Although previous research suggests that STEM teachers are more likely to use data for instructional purposes (Hill et al., 2020), our findings show that languages, arts, and humanities teachers, and even more so teachers in vocational subjects — not included in previous studies — tend to report higher digital data use. One possible explanation is that the curriculum and pedagogical practices in different subjects, in particular vocational education, may involve more frequent use of digital platforms (Cattaneo et al., 2025) and data-driven tools. Vocational school curricula often integrate more practice-based activities closely linked to work environments. Further research is needed to explore how subject-specific differences impact the adoption of learning analytics in schools.

Additional teacher characteristics included in our analysis, such as age and gender, did not affect the use of digital data. However, years of teaching experience had a minor negative predictor. This may reflect that less experienced teachers might feel more comfortable adopting new digital practices, while more experienced teachers may be hesitant due to established teaching practices, a tendency noted in previous studies (Ertmer & Ottenbreit-Leftwich, 2010; Mavroudi et al., 2021). However, the overall impact of teaching experience on digital data use appears limited, suggesting that teacher competencies and attitudes are more critical predictors.

Another main finding is that teachers from different schools significantly differed in the use of digital data. Although only 11% of the variance in digital data use was attributed to differences between schools, this result suggests that it is worth exploring the school context influencing digital data use. For this reason, we further examined different school-related factors (RQ2) and whether teacher characteristics mediated digital data use (RQ3), as previous research with technologies or data use in schools suggested this mediation (Fang et al., 2024; Håkansson Lindqvist, 2019; Petko et al., 2018; Timotheou et al., 2023). School-related factors — including ICT importance, school principal support, goal clarity, and informal and formal collaboration on digital technologies — had a miniscule direct impact on digital data use. As we initially expected, these school-related factors were mediated by teacher characteristics concerning their positive beliefs about digital technologies, their skill in using digital data, and the reported availability of data technologies (will-skill-tool variables). This mediation model explained 50% of the variance in digital data use. This result mirrors previous findings investigating school-related factors in data use (Schildkamp, 2019; Vanlommel & Schildkamp, 2019; Lockton et al., 2020) and digital technologies in schools (Håkansson Lindqvist, 2019). It also confirms that the school-related factors are mediated by teacher characteristics in the case of data technologies, as previously found in the case of digital technologies in general in schools (Fang et al., 2024; Inan & Lowther, 2010; Petko et al., 2018). Additional factors that could explain the other 50% could be integrated into the model, such as school culture and professional development programs on data use (Schildkamp, 2019).

The main conclusion of our study is that the use of digital data by teachers is not solely influenced by school factors or teacher characteristics but rather by a combination of both. Understanding teacher characteristics, such as those related to the will-skill-tool variables, is crucial for adopting digital data use. However, it is equally important to explore how these teacher characteristics can be strengthened through school-related factors such as informal and formal collaboration among teachers and school principal support (Krumm et al., 2018). Promoting collaboration and continuous professional development within schools is important in enhancing teachers' digital practices. Facilitating both formal and informal collaboration can help teachers share experiences and increase their confidence in using digital data effectively. Moreover, strong leadership support, including professional development opportunities and clear goals for digital data integration, could make teachers feel equipped to incorporate data into their teaching practices.

These results regarding school factors align with research on organizational challenges in the context of learning analytics in schools, which emphasizes the involvement of various stakeholders — including school leaders, teachers, and local policy makers — in the decision-making process (Jimerson and Childs, 2017; Ifenthaler, 2021; Sergis and Sampson, 2016). Our study suggests that organizational factors about schools should be studied in relation to the diverse teacher characteristics that influence digital data use, such as teacher skills and the subjects they teach (Hase et al., 2022; van Leeuwen et al., 2021; de Sousa et al., 2021). This is also related to the distinction between macro (government, institutional), meso (school, class), and micro (student, activity) levels of learning analytics (Buckingham Shum, 2012). Future research on learning analytics in schools could further investigate how teacher and school factors influence student outcomes at the meso level.

This study has several limitations, including the reliance on self-reported data from the online teacher survey. Further studies can evaluate teachers' classroom practices with digital data or learning analytics tools with other objective measurements (e.g., observational studies or mixed-method approaches) considering our main findings. The survey included items for both the use of digital technologies and the use of digital data. Further evaluations might focus solely on digital data or include more items in the evaluation of the will-skill-tool variables, as our survey had length restrictions. Using single items to assess some variables may have constrained the reliability and granularity of these measures. Future studies could expand these items for a more nuanced understanding of the variables, especially regarding the "skill" dimension of the WST model and the use of digital data. Including a longitudinal study design could help understand how teacher practices evolve over time. Additionally, we asked teachers about digital data in general, without considering the differences, for example, in the use of student progress data and student assessment data to inform their teaching. Thus, future research might differentiate the types of data collected in digital platforms and understand their use by teachers. Notably, ethical considerations such as data privacy, informed consent, and the responsible use of student information in learning analytics should also be more thoroughly examined (Beardsley et al., 2019). As digital data becomes increasingly embedded in classroom practice, future work could explore how teachers navigate different ethical concerns (e.g., privacy, ownership, fairness) in learning analytics (Tzimas & Demetriadis, 2021), how well they are supported by schools, and what training is needed to ensure digital data use aligns with ethical standards.

Our sample of teachers in Switzerland may limit the generalizability of the findings, as technological infrastructure and teacher attitudes can vary both across and within countries. Regional differences such as variations in policies, school culture, ICT infrastructure, and leadership practices might influence the results and require further investigation. Expanding the study to include more teachers and schools from other countries (Aguerrebere et al., 2022) could provide a more comprehensive picture of digital data use in schools. Additionally, while school factors such as ICT importance and leadership support were included, schools likely vary widely in these aspects. Qualitative data collection with case studies could provide further insights and help interpret quantitative findings. This study employed a one-level SEM approach with cluster robust standard errors to account for the nested structure of the data. However, this approach does not fully address the multilevel nature of teacher- and school-level factors. Using a multilevel SEM in future research could provide a deeper understanding of the interactions between these levels.

Despite these limitations, the study provides valuable insights into the interplay between teacher- and school-related factors in the use of digital data in schools, establishing a basis for further research and practical improvements in in this area. One main strength of our study is the inclusion of a large number of teachers (N = 2,247) across different cantons, school types, and teaching subjects in Switzerland.

7. Implications

Our study has several implications for research and practice in the field of learning analytics in schools. Based on our results, we suggest four directions for future work and practical applications.

7.1. Exploring Teacher Characteristics Based on the Will-Skill-Tool Model

Further research could continue exploring teacher characteristics using the will-skill-tool model in the context of learning analytics in schools. More specifically, future studies could investigate how enhancing teacher beliefs about digital technologies might also influence their skills in using digital data. Additionally, it is important to assess the availability of data technologies across different schools to better understand how varying levels of technological access impact teacher engagement with digital data. This line of investigation could also clarify whether the type of available platform (e.g., learning management systems, dashboards) influences how teachers use digital data. Furthermore, examining differences across teaching subjects might enhance the credibility and practicability of learning analytics in schools, as we found differences in digital data use between subject-specific teachers.

7.2. School-Related Factors and Personalized Recommendations

School-related factors such as ICT importance, school principal support, and goal clarity were found to influence digital data use, but this was mediated by teacher characteristics. Future research could evaluate how school factors can be integrated with teacher-specific characteristics (such as their data literacy or beliefs) to formulate more targeted, personalized recommendations for digital data use. For instance, schools could develop subject-specific professional development programs (Darling-Hammond et al., 2017) that focus on how to effectively use digital data in teaching, aligning with teachers' individual needs and the contextual demands of their subjects. These programs could also incorporate case studies or practical examples to demonstrate how learning analytics tools can be used to inform instructional practices.

7.3. Systemic and Human-Centred Approach to Learning Analytics

Following the research on human-centred learning analytics (Buckingham Shum et al., 2019), we suggest that the use of digital data in schools should be understood as a systemic issue that involves both school and teacher characteristics. Our study points to the need for a broader framework that considers the school context, leadership support, and teacher collaboration alongside teachers' technical skills and beliefs. Practical recommendations for schools could focus on fostering a culture of collaboration where teachers are encouraged to share their experiences using data technologies and to work together on data-driven teaching initiatives. Collaborative initiatives, such as mentoring or data sharing workshops (Michos et al., 2020), could be effective in building teacher confidence and facilitating the use of digital data in the classroom.

7.4. Integrating AI and Emerging Technologies into Professional Development

As AI technologies continue to evolve, their potential to enhance data use in schools becomes increasingly significant. AI-powered tools, such as personalized learning platforms, can help teachers analyze and interpret data more efficiently, offering real-time insights to inform instructional decisions. Schools and teachers could consider integrating AI technologies with professional development initiatives to further enhance teacher data literacy and enable more effective use of digital data. However, the integration of AI should be done thoughtfully, ensuring that teachers are adequately trained to use these tools and that the ethical implications of AI, such as data privacy and bias, are carefully considered (Zhang & Zhang, 2024).

Declaration of Conflicting Interest

The authors declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

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