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Implementation of technology-supported personalized learning—its impact on instructional quality

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ABSTRACT

Digital technology especially raised hopes to open up new possibilities to personalize learning. Although various schools have implemented approaches of technology-supported personalized learning, the impact on instructional quality remains unclear. As a common definition of the multilayered construct *personalized learning* is lacking, our study focuses on two theoretical dimensions of technology-supported personalized learning to investigate the impact on instructional quality. For this purpose, our study has analyzed data from a survey of N = 860 students (8th grade) from 31 Swiss schools with personalized learning concepts. Results show that student-centered teaching methods in the context of technology-supported personalized learning stimulate the cognitive activation of the students, and the supportive climate increases slightly with a higher degree of students' voice and choice on the computer.

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Instructional quality; personalized learning; student-centered perspective; technology

Introduction

Personalized learning as a student-centered approach is called for to better align instruction to students' individual needs and prior experiences (Murphy et al., 2016; Reigeluth et al., 2017). This idea has existed for a long time and several educational endeavors have tried to implement it with different learning philosophies (e.g., behaviorist, cognitivist and constructivist learning theories). However, the implementation of this idea remains a big challenge. Especially in the last 15 years, the approach of personalized learning has gained popularity, mainly in Anglo-American countries (e.g., Bray & McClaskey, 2015; Miliband, 2006; Pane et al., 2017; Zhang et al., 2020). Although neither student-centeredness nor personalized learning are new research topics, publications on research to personalized learning have increased significantly since 2008 according to a recent review of the literature (Shemshack & Spector, 2020). Digital technology particularly raised hopes to open up new possibilities to personalize learning. Therefore, the approaches are at present often discussed in relation to digital technology. Various studies investigated the role of specific digital tools and systems to personalize learning (Gierl et al., 2018; Lee et al., 2018; McLoughlin & Lee, 2010; Zhang et al., 2020). However, the impact of implemented approaches of technology-supported personalized learning on educational outcomes has been investigated rarely so far (Lee et al., 2021; Shemshack & Spector, 2020; Zhang et al., 2020). For example, intelligent tutoring systems are one important stream of the existing research (Crow et al., 2018; Kulik & Fletcher, 2016; Ma et al., 2014). This kind of computer programs provides individualized instruction based on computational algorithms or models without the intervention of teachers. With regards to practice, many schools have implemented a whole-school approach of personalized learning, using multiple technological tools to tailor teaching and learning to the individual needs of students and to increase student choice, especially in Europe (Petko et al., 2017; Schmid & Petko, 2019). However, studies have so far rarely investigated the impact of technology-supported personalized learning as a whole-school approach on educational outcomes (Lee et al., 2021; Shemshack & Spector, 2020; Zhang et al., 2020). Although many schools have changed their teaching practices, it is still unclear whether the general use of digital technology to support personalized learning settings have an effect on the quality of instruction.

One difficulty is associated with the operationalization of personalized learning as a complex and multilayered concept. As the research literature shows, a wide variety of dimensions are subsumed under the concept, and the implementation in practice is rather heterogeneous (Keefe, 2007; Shemshack & Spector, 2020; Stebler et al., 2018). To constrain the conceptual fuzziness, the present study analyses two dimensions of computer-supported personalized learning—*student-centered teaching methods* and *students' voice*

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and choice in technology-supported personalized learning. The aim of the study is to examine the impact of these two dimensions on the instructional quality as an important mediator of educational outcomes.

In the following, the theoretical background for this study will be presented. First, we present the approach of personalized learning and its relevance in the context of technology. Second, we provide an overview of the current research on the effects of technology-supported personalized learning on educational outcomes. Finally, we describe a widely used conceptualization of the construct of instructional quality in the German-speaking area and explain the effects of technology-supported personalized learning on instructional quality.

Literature review and theoretical framework

Personalized learning and technology

Besides the call to tailor teaching to the individual needs and prior experiences (Murphy et al., 2016; Reigeluth et al., 2017), students must be at the center and active (Bray & McClaskey, 2015; Sebba et al., 2007). These are important preconditions for optimal outcomes of learning. Regarding the published research, the approach of personalized learning has increasingly gained more attention (Shemshack & Spector, 2020), and it is often built on the help of technology (Attwell, 2007; Bingham et al., 2018; Lee et al., 2018; Murphy et al., 2016). Different English-speaking countries, such as the United States, United Kingdom, and Canada, have initiated educational reforms toward personalized learning (Basham et al., 2016; Sebba et al., 2007; Zhang et al., 2020). In Europe, the term *personalized learning* is less established compared to the English-speaking countries. With a view to the school field, for example in Switzerland, several public and private schools have independently introduced forms of personalized learning, often supported by technology (Petko et al., 2017; Schmid & Petko, 2019).

Despite this growing interest across the countries, current systematic research reviews on the implementation and on the definition of the term *personalized learning* show different emphases and demonstrate that a common operationalization of the approach is absent (Shemshack & Spector, 2020; Zhang et al., 2020). Nonetheless, a common overarching idea behind all definitions can be found and can be described as follows: The implementations in practice show a shift toward a broad array of *student-centered teaching methods* that include higher degrees of student self-direction compared to traditional teacher-centered instruction. At the same time, appropriate teacher guidance is an important part of student-centered learning with regard to the effectiveness (Drexler, 2010; Lazonder & Harmsen, 2016). Due to this shift, students have a more active role in personalized learning settings than in traditional learning settings, which gives students a say—*students' voice and choice*—in learning (Bray & McClaskey, 2015; Jones & McLean, 2012; Miliband, 2006; Mötteli et al., 2021; Schmid & Petko, 2019; Watson & Watson, 2017). Within curricular guidelines, students' voice and choice can relate to what, when, and how they learn. Further, students can co-determine the social organization and the assessment of the learning process. The active involvement of the students through their voice and choice can be considered as a key differentiator from other related concepts, such as individualization and differentiation (Bray & McClaskey, 2015; DeMink-Carthew & Netcoh, 2019). The National Personalized Learning Scan of the United States shows that giving students more control of pacing content and learning activities is one of the biggest challenges in the transition toward personalized learning. This challenge is reflected in a strong reluctance to cede control to students (Gross et al., 2018).

In the implementation of personalized learning settings, technology can be significantly supportive. Lee et al. (2018) argue that to personalize instruction and to document the individual learning progress, technology is essential. Their study of the functions of technology in personalized learning showed that technology is currently used primarily for lesson planning and instruction (Lee et al., 2018). In general, the organization and management of personalized learning settings are becoming more complex than in traditional learning settings. Compared to traditional learning settings where teachers have for the most part given the same task to all students at the same time, the teaching methods in personalized learning settings are student-centered. This means students solve different tasks with different performance levels at different times of their own choosing, which is more demanding to organize and manage. However, by implementing technology, the increased complexity can be managed, for example, through a better overview of the individual tasks and the processing status. On the one hand, this overview helps the teacher to recognize individual needs of students for support at an early stage, despite the individual assignment of tasks and processing status (Reigeluth, 2017), and on the other hand, it helps the individual student to keep track of their individual tasks with different submission dates (Schmid et al., 2022). Thus, technology can enable personalized learning settings by mastering the organization and management of personalized learning plans. With regard to students' voice and choice, technology provides a greater range of information, especially due to the internet (e.g., Sebba et al., 2007). This can help teachers to develop tasks with individual content choice on one hand and tasks with authentic problems on the other hand, which would not be possible in this form without technology. If students can learn with authentic problems or can choose the content within a task adapted to their individual interests, learning becomes more relevant, which has the potential to increase the learning outcome (Walkington & Bernacki, 2018). At the same time, this means that students must learn at school how to use the internet, for example, how to find the desired information on the internet.

The required prior knowledge in dealing with technology shows that, along with the advantages, there are also certain challenges to be considered. For example, a good infrastructure including sufficient internet bandwidth and a school-wide IT concept are important preconditions (Bingham et al., 2018). However, a high standard of infrastructure does not automatically lead to a more intensive or effective integration of technology (Niederhauser et al., 2018). Different studies show that teachers' individual beliefs about the use of technology play a critical role in whether they regularly use technology in the classroom and in how effectively they use it (Ertmer et al., 2012; Hermans et al., 2008; Petko, 2012). Finally, students need specific introductions to each digital tool and assistance in completing tasks on the computer (Schmid et al., 2022).

Effects of technology-supported personalized learning approaches on educational outcomes

While positive effects of technology-supported personalized learning approaches on educational outcomes have been often proposed from a theoretical perspective, empirical evidence is still in its infancy. Shemshack and Spector (2020) described it as challenging to find "a sufficient number of published cases that report effect sizes" to conduct a meta-analysis on personalized learning environments that are among other factors "effective and efficient in supporting and promoting desired learning outcomes" (p. 2). Lee et al. (2021) support this evaluation with the conclusion that scarce studies have investigated the practice of personalized learning in relation with academic achievement. However, a research review on the implementation of personalized learning showed that 50 out of 71 studies investigated a specific tool or digital system to enable personalized learning (Zhang et al., 2020). The majority of these studies were associated with positive findings among others in terms of academic outcome and engagement (e.g., Arroyo et al., 2014; Walkington, 2013). Meta-analyses of intelligent tutoring systems (ITS) indicate positive effects on student outcomes when compared to non-individualized forms of teacher-guided instruction or non-ITS educational software (Kulik & Fletcher, 2016; Ma et al., 2014). However, the development costs of ITS are immense and only few systems are available for highly specific curricular topics. A recent systematic review of the conceptual trends of technology-supported personalized learning corroborates a positive trend on learning outcomes (Van Schoors et al., 2021). Further, the research reviews pointed out that only a few studies evaluated the practice of technology-supported personalized learning as a comprehensive school-wide approach and its effect on educational outcomes (Van Schoors et al., 2021; Zhang et al., 2020).

Two national large-scale studies of the United Kingdom investigated practices of personalized learning in the context of the educational strategy. Sebba and his colleagues (2007) analyzed how schools implemented personalized learning initiated by the Five Year Strategy for Children and Learners in 2004 (Department for Education and Skills and Great Britain (DfES),), 2004). About half of the schools used technology for assessment, but otherwise the interplay between educational effectiveness and personalized learning with technology was not explored in detail (Sebba et al., 2007). The other study analyzed questionnaires of 67 schools and conducted case studies of 24 schools (Underwood et al., 2007). According to the case studies, students used computers for collaborative learning and online self-assessment, and teachers used computers for computer-based instruction. However, the data from the questionnaires indicated no statistically significant correlation between high-performing secondary schools and a high degree of personalization according to the agenda of the schools. Further, a recently published study of the United States investigated personalized learning approaches and technology in relation to students' performance (Lee et al., 2021). Survey data of 72 learner-centered schools and standardized test results were analyzed. Teachers in high-performing schools used technology for more functions and implemented personalized learning more comprehensively compared to low-performing schools (Lee et al., 2021). To strengthen this finding, it would be necessary to control for context factors, as for example IT infrastructure, or the rate of free and reduced lunches (FRL rate), which was higher in the low-performing group.

When looking at the effectiveness of student-centered approaches in general, two meta-analyses studies showed that student-centered approaches are associated with an increase in cognitive and in emotional-social aspects of learning in comparison to traditional approaches (Cornelius-White, 2007; Freeman et al., 2014). Other review studies questioned the effectiveness of minimally guided instruction approaches (Hattie, 2009; Sweller et al., 2007). At present, there is a distinct shift toward student-centered teaching methods supported by technology that offer an appropriate combination of student self-direction and teacher support (Lazonder & Harmsen, 2016; Petko et al., 2017; Stebler et al., 2018).

Overall, limited empirical research exists, especially for technology-supported personalized learning analyzed as a whole-school approach. The existing body of research is partly inconsistent, which is probably due to differences in teaching and learning quality. However, there is preliminary evidence that technology-supported personalized learning—implemented in a qualitatively satisfying way—has a moderate positive effect on educational outcomes (Lee et al., 2021; Van Schoors et al., 2021; Zhang et al., 2020). Since the quality of instruction is crucial with regard to student outcomes (Baumert et al., 2010; Creemers & Kyriakides, 2008; Decristan et al., 2015; Fauth et al., 2014; Hattie, 2009; Lipowsky et al., 2009), it seems beneficial to analyze the impact of technology-supported personalized learning on instructional quality.

Effects of technology-supported personalized learning approaches on instructional quality

There exist several frameworks on instructional quality with large overlaps (e.g., Pianta & Hamre, 2009; Praetorius et al., 2018; Roloff et al., 2020; Seidel & Shavelson, 2007). In Europe, especially in the German-speaking countries, a three-component framework has been established. The so-called three basic dimensions, namely *cognitive activation*, *supportive climate*, and *classroom management*, are often used in empirical analysis to define and operationalize the quality of instruction (e.g., Fauth et al., 2014; Klieme et al., 2001; Lipowsky et al., 2009). Although the three dimensions were originally identified in mathematics education with traditional learning settings based on the large-scale study TIMSS 1995 (Third International Mathematics and Science Study), the conceptualization of the dimensions in terms of content is largely subject-independent and not related to the method of instruction.

Despite ample research on the three dimensions of instructional quality and their impact on student outcomes, empirical research on the relationship between technology-supported personalized learning approaches and instructional quality is absent. When considering the research on the three generic dimensions of instructional quality, the following impact of technology-supported personalized learning on the three dimensions can be assumed:

The first dimension, *cognitive activation*, involves providing tasks and questions that require students to activate their prior knowledge and use it to access new content. In cognitively challenging instruction, the teacher asks students, for example, to elaborate on their way of thinking or to relate statements in discussions. Enhancing a deep understanding of the concepts is a continual focus (e.g., Baumert et al., 2010; Fauth et al., 2014; Klieme et al., 2009; Lipowsky et al., 2009; Praetorius et al., 2018). It can be assumed that technology-supported personalized learning enhances cognitive activation, since the individual levels of each student, such as prior knowledge or interests, can be better taken into account than in traditional learning settings (e.g., Walkington, 2013). This allows deep learning to occur at different levels, as we have described in the first section of this literature review.

To achieve the goal of deep understanding, students need a supportive environment in addition to cognitively challenging learning activities. This second dimension of *supportive climate* covers appropriate teacher support for comprehension problems of students and a high level of teacher sensitivity regarding the individual needs of students. A positive teacher–student interaction enables the creation of a supportive environment in which students can feel safe (e.g., Fauth et al., 2014; Lipowsky et al., 2009; Praetorius et al., 2018). It can be assumed that teacher support increases in computer-supported personalized learning. By opening up instruction with transfer of control to students, digital tools are often implemented to manage the personalized learning plans. Thereby the individual processing status of each student and their problems with tasks becomes visible at an early stage (e.g., Reigeluth, 2017). Due to this technological support, teachers obtain more indications on diagnostics, and thus students receive the individual teacher support that they need during the self-directed learning phases. Further, some students will need more help and guidance to be able to solve their tasks individually on the computer than in traditional learning settings (e.g., Lazonder & Harmsen, 2016).

The third dimension represents the *classroom management*. The focus here is on managing the lesson effectively to ensure that as few disruptions as possible occur. Teachers must ensure that students are on-task, and thus all students use the available time of class for learning. An effective use of the teaching time requires a high clarity of rules, monitoring students' behavior, and enforcing the rules when necessary (e.g., Emmer & Stough, 2001; Kounin, 1970; Pianta & Hamre, 2009). Although good classroom management is crucial for students' learning gains, technology-supported personalized learning, for example, does not facilitate the clarity of rules. Since the complexity of personalized learning settings supported with students' co-determination tends to increase, but so does the potential to use the learning time effectively, no positive reinforcement of technology-supported personalized learning on classroom management is assumed.

These three dimensions of instructional quality represent a parsimonious but relatively comprehensive systematization of the teaching and learning processes that can be observed in the classroom (Klieme, 2019; Kunter & Ewald, 2016). However, empirical clarification is needed to verify the assumptions of whether student-centered teaching methods and students' voice and choice in technology-supported personalized learning correlate positively with the quality of instruction.

Research questions

To address the dearth of research as presented in the previous section, the present study investigated implemented technology-supported approaches of personalized learning combined with instructional quality (i.e., the three subdimensions of cognitive activation, supportive climate, and classroom management). The purpose of the study is to consider the dimensions *student-centered teaching methods in technology-supported personalized learning* (TEME) and *students' voice and choice in technology supported personalized learning* (VOCH) and whether these dimensions have a positive impact on the instructional quality operationalized by the three subdimensions.

Taking account of the current state of the research so far, which we have described in the previous section, we will investigate the following three research questions:

> (RQ1) Are *student-centered teaching methods in technology-supported personalized learning* (TEME) and *students' voice and choice in technology-supported personalized learning* (VOCH) statistically significant positive predictors of cognitive activation, (RQ2) and of supportive climate based on students' assessments?

> (RQ3) Do *student-centered teaching methods in technology-supported personalized learning* (TEME) and *students' voice and choice in technology-supported personalized learning* (VOCH) influence classroom management based on students' assessments?

The proposed theoretical assumptions are visualized in Figure 1.

Methodology

Contextualization of the study

A growing number of Swiss schools have been changing their culture of teaching and learning by implementing a form of personalized learning. The perLen ("Personalized

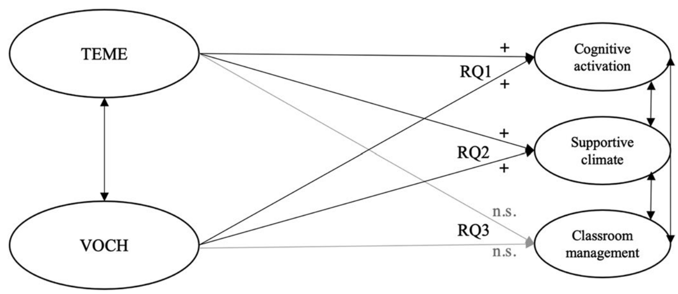

Figure 1. Hypothesized structural equation model.
Note. TEME = Student-centered teaching methods in technology-supported personalized learning, VOCH = Students' voice and choice in technology-supported personalized learning

Learning Concepts in Heterogeneous Learning Groups") research project investigated such schools in the German-speaking part of Switzerland over three years (2013–2015) (Stebler et al., 2018). Our present study formed part of this project.

Although the implementation of personalized learning inevitably differs between the 31 participating lower-secondary schools, there is sufficient evidence for common characteristics. All schools have developed their teaching in the following areas: student-centered teaching methods, self-directed learning, and adaptive learner support. For this purpose, they have rescheduled their weekly lesson plans and integrated time slots for autonomous student learning. During these self-directed learning phases, students follow a personal learning plan, whereby they typically have more choice and voice concerning what, how, and when they learn than in traditional classroom settings. As a consequence, the role of the teachers primarily consists in supporting. Many students have one-on-one meetings with their teacher to discuss difficulties and the general workflow of the self-directed learning phases. Finally, all schools developed their teaching culture in a bottom-up initiative, mostly with the aim of better catering to heterogeneous groups of students.

Regarding the use of digital technology, computers and sometimes laptops with internet access are available in the open learning space. Although the frequency and method of implementation varies widely, students use computers for individual learning tasks, especially during the self-directed learning phases. Due to the limited infrastructure, teachers sometimes specify for which assignments the computer may be used. In addition to word processing and presentation programs, subject-specific learning software is also used, which is developed together with newer mandatory teaching materials, e.g., in mathematics. Particularly in vocational education, a specific online platform named yousty is perceived as a great added value. Adaptive technologies, on the other hand, are hardly implemented yet. However, many schools employ a learning platform to administer personalized learning plans. A detailed description on the integration of the different technological tools is provided in the multiple case studies from Schmid et al. (2022).

Ethical considerations

The data collection of the present study has been conducted following the ethical requirements established by the Swiss Academies of Arts and Sciences. Consequently, all data analyses were conducted based on anonymous data.

Sample

This cross-sectional study is based on a student survey in schools that have introduced personalized learning concepts. The analysis relates to the $N = 31$ lower-secondary schools with $N = 1017$ 8^{th}-grade students (486 female, 531 male students) from 78 classes. Only students who reported using technology in class at least sometimes were asked about their user behavior in more detail. Therefore, we excluded students with non-answers. The final data set consisted of $N = 860$ students. 48.7% (419) were female students. The median of the students' year of age was fourteen, with an interquartile range of six years.

All 31 schools were recruited by an open call for schools with personalized learning concepts or had been invited because of recommendations from Swiss municipal and cantonal education departments. Participation was voluntary. The sample cannot be considered representative; however, all schools have been developing their teaching in the direction of personalization. A more detailed description of the common characteristics of personalized learning that become manifest in these schools is available from Schmid and Petko (2019).

Data collection and study measures

To answer our research questions, we surveyed students to gain direct insight into how the technology-supported personalized learning units are implemented. The self-estimated frequency of personalized learning activities supported by technology, together with the perceived instructional quality based on the three subdimensions were assessed via standardized online questionnaires, which took place during regular lessons. This student questionnaire was part of the survey in 2013 of the perLen project and had been devised on the basis of existing instruments.

Instructional quality was assessed with ten items (IQUAL) and consisted of three subdimensions: classroom management (3 items, e.g., "In class, everyone knows the rules that must be followed."), cognitive activation (3 items, e.g., "My teachers want me to be able to explain my answers."), and supportive climate (4 items, e.g., "My teachers know what I'm already good at."). The short scales were developed on the basis of the inventory of Bos et al. (2011) and Fauth et al. (2014). All items were assessed on a 4-point Likert-type scale, ranging from 1 (*strongly disagree*) to 4 (*strongly agree*). All questions used for instructional quality are documented in the Appendix.

Regarding the validity of instructional quality, Fauth et al. (2014) assessed the factorial validity and the predictive power of the student ratings of the instructional quality.

The results provided evidence for a valid three-dimensional framework of instructional quality. In addition to Fauth et al. (2014), Praetorius et al. (2018) reported that various studies could confirm the factorial validity of the three subscales on teaching quality.

The construction of the latent independent variables *student-centered teaching methods in technology-supported personalized learning* (TEME, 3 items, e.g., "I work with my weekly or daily learning plan on the computer.") and *students' voice and choice in technology-supported personalized learning* (VOCH, 3 items, e.g., "I decide the procedure on the computer myself.") was grounded in theory and is based on Schmid and Petko (2019). All items were assessed on a 4-point Likert-type scale (*almost* daily, 1 to 2 times per week, 1 to 2 times per month, *almost* never). All questions used for technology-supported personalized learning are documented in the Appendix.

Data analysis

To answer our research questions, we employed a structural equation modeling approach with latent variables (Kline, 2015; Schreiber et al., 2006). Before modeling the structural equation model, we tested the measurement model *instructional quality* besides the two theory-based factors of personalized learning with confirmatory factor analysis and tested their reliability estimates with McDonald's omega (ω) (Hayes & Coutts, 2020). To evaluate the fit of the confirmatory factor models and the structural equation model, we examined the typical goodness-of-fit indices. As typical indices, we report χ^2 values, the comparative fit index (CFI) and Tucker–Lewis index (TLI) with minimum cutoff criteria of ≥ .90 or .95, the root mean square error of approximation (RMSEA) ≤ .05 or .08, and the standardized root mean square residual (SRMR) ≤ .08 or .06 (Hu & Bentler, 1999).

The measurements of the structural equation model were estimated by using the robust maximum likelihood (MLR) method to consider possible non-normality problems, and missing patterns were treated with a full information maximum likelihood (FIML) approach. Although there might have been little variance between the schools, it was not possible to apply multilevel modeling. The sample consisted of too few schools relative to the number of parameters. However, the intraclass correlation coefficients of the dependent variables were relatively low (ρ = 0.04–0.28), and thus the multilevel approach was not necessarily required. All analyses were carried out with R version 4.0.2 and the packages lavaan, lavaan.survey, and psych (Beaujean, 2014; Revelle, 2017; Rosseel, 2012).

Results

Descriptive analysis

The internal consistencies, means, standard deviations, and intercorrelations of the independent key variables (TEME and VOCH) and instructional quality including all three subdimensions (IQUAL) are shown in Table 1. The reliabilities of the presented scales were acceptable to good with McDonald's ω from .68 for student-centered teaching methods in computer-supported personalized learning to .82 for students' voice and choice in computer-supported personalized learning. On average, students reported using digital technology monthly for learning plans or project work (TEME, $M = 2.10$, $SD = 0.77$). On a nearly weekly basis on average, students stated that they can determine their procedure, time management, and learning content on the computer (VOCH, $M = 2.87$, $SD = 0.81$). Further, students agree to receive learning support in completing demanding tasks and to adhere the rules in class (IQUAL, $M = 3.27$, $SD = 0.35$). All intercorrelations of the variables were positive and statistically significant.

First, we examined the two factors of personalized learning, namely student-centered teaching methods in computer-supported personalized learning (TEME) and students' voice and choice in computer-supported personalized learning (VOCH) as latent and correlated factors by a confirmatory factor analysis. The results showed a very good fit to the data (Chi^2(7) = 26.656, CFI = .98, TLI = .96, RMSEA = .057, SRMR = .028). Thus, this two-factor model represented the data well.

In a second step, we examined *instructional quality* modeled by three latent factors: *classroom management*, *cognitive activation*, and *supportive climate*. The confirmatory factor analysis confirmed the measure model with good fit values whereby no modifications were needed (Chi^2(32) = 61.483, CFI = .98, TLI = .97, RMSEA = .03, SRMR = .03). The subdimensions of cognitive activation (3 items, McDonald's ω = .64) and supportive climate (4 items, McDonald's ω = .72) showed acceptable reliabilities. However, the reliability of the classroom management subscale, operationalized by three items, was not sufficient (McDonald's ω < .6). To improve the reliability by a deletion of an item was not possible. Nevertheless, classroom management is an essential aspect of instructional quality for crafting validity, as it establishes the internal structure of the theoretical construct (Fauth et al., 2014). Based on the evidence, and to better understand the influences on instructional quality, we have analyzed the three subdimensions in the structural equation model as latent factors in a differentiated way. However, the results of the classroom management subdimension must be interpreted with caution.

Structural equation modeling

To examine our proposed theoretical assumptions presented in Figure 1—the impact of the two important aspects of computer-supported personalized learning TEME and VOCH on the three sub-dimensions of instructional quality—we specified a structural equation model with the previous tested measurement models (see previous section). The model considered TEME and VOCH as correlated predictors of the subdimensions of instructional quality as dependent variables (see Figure 2). The structural equation model exhibited a good fit to the data and no modification indices

Table 1. Internal consistencies, means, standard deviations, and intercorrelations of the independent key variables and instructional quality.

Variable	McDonald's ω	Mean (*SD*)	1	2	3
1 TEME	.68	2.10 (0.77)	–		
2 VOCH	.82	2.87 (0.81)	.38***	–	
3 IQUAL	.76	3.27 (0.35)	.13***	.14***	–

Note. $N = 860$. Reported coefficients are product-moment correlations; *** $p \leq .001$.
TEME = Student-centered teaching methods in technology-supported personalized learning, 1 = (almost) never – 4 = (almost) every day; VOCH = Students' voice and choice in technology-supported personalized learning; 1 = (almost) never – 4 = (almost) every day; IQUAL = Instructional quality; 1 = totally disagree – 4 = totally agree.

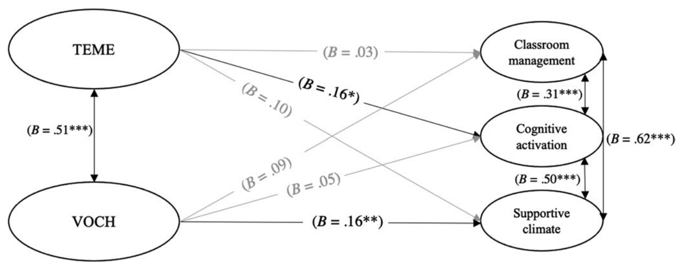

Figure 2. Structural equation model describing TEME and VOCH as predictors of the three subscales of instructional quality.
Note. $N = 860$; fit values: $\chi^2(91) = 154.896$, CFI = .96, TLI = .95, RMSEA = .03, SRMR = .03; *** $p \leq .001$. TEME = Student-centered teaching methods in technology-supported personalized learning, VOCH = Students' voice and choice in technology-supported personalized learning.

were needed ($Chi^2(91) = 154.896$, CFI = .96, TLI = .95, RMSEA = .03, SRMR = .03).

In regard to the structural equation model, both factors of technology-supported personalized learning had a statistically significant impact on one subdimension of instructional quality (see Figure 2). VOCH had a statistically significant, though moderate, positive effect on the supportive climate ($\beta = .16$, SE = 0.03, $p < 0.01$) and did not correlate with the other subdimensions. TEME was a positive predictor of students' cognitive activation ($\beta = .16$, SE = 0.03, $p < 0.05$). The impact of TEME on the other subdimensions of instructional quality was close to zero and not statistically significant. The regression coefficient of VOCH on supportive climate had a higher level of significance than TEME on cognitive activation. All subdimensions of instructional quality were highly statistically significantly and positively correlated. At the same time, the relation between the two aspects of technology-supported personalized learning TEME and VOCH was strongly positive and statistically significant ($\beta = .51$ SE = 0.03, $p < 0.001$).

Discussion

Technology-supported personalized learning as a whole-school approach has been often proposed as beneficial for educational outcomes from a theoretical perspective; however, empirical evidence is still in its infancy (Lee et al., 2021; Shemshack & Spector, 2020; Zhang et al., 2020). Due to the need for more evidence in this area of empirical research, our study looked at the correlation between technology-supported personalized learning and the quality of instruction perceived by the students based on three subdimensions. To operationalize the multilayered construct of technology-supported personalized learning, we have focused on two dimensions, *student-centered teaching methods* and *students' voice and choice* in technology-supported personalized learning.

The analyses have shown that both dimensions influence statistically significantly positive one subdimension of instructional quality; student-centered teaching methods in technology-supported personalized learning stimulate the cognitive activation of the students in tendency ($B = .16$, $p \leq 0.05$), and the supportive climate increases slightly with a higher degree of students' voice and choice on the computer ($B = .16$, $p \leq 0.01$). However, both effect sizes are moderate. All other effects of technology-supported personalized learning on the sub-dimensions of instructional quality are negligible and do not reveal significance. In contrast, the two dimensions of technology-supported personalized learning are strongly correlated ($B = .62$, $p \leq 0.001$); student-centered teaching methods are therefore closely linked to students' voice and choice in technology-supported personalized learning, and vice versa.

Regarding our third research question, technology-supported personalized learning, as we proposed, does not lead to perceived higher quality of classroom management (RQ3). This seems to be conclusive, as the teacher may need to demand the desired behavior of the students in technology-supported personalized learning settings as well as in traditional forms of teaching to ensure an effective use of learning time (Klieme, 2019; Kounin, 1970). The complexity of personalized learning settings supported with students' co-determination even tends to increase, especially during the self-directed learning phases. Thus, the classroom management becomes more demanding, although the computer-supported personalized learning favors an effective learning time (Gross et al., 2018; Lee et al., 2021; Postholm, 2013).

When looking at cognitive activation, we expected an increase, which is partly supported by our data (RQ1). With student-centered teaching methods supported by technology, teachers tend to succeed in assigning cognitively challenging tasks that stimulate each student in deeper thinking and understanding ($B = .16$, $p \leq 0.5$). This result is in line with existing research that shows student-centered learning environments can foster cognitive aspects in learning, provided adequate teacher guidance (Freeman et al., 2014; Lazonder & Harmsen, 2016). Further, the integration of digital technology can help to provide individual challenging tasks (Reigeluth, 2017). Previous findings of international studies have shown that students use digital technology more frequently in student-centered learning environments compared to conventional learning settings (OECD, 2015;

Schmid & Petko, 2019; Tondeur et al., 2017). However, it is not the frequency of technology use that is decisive but a qualitative way of implementation, which these data confirm with regard to the mere monthly use of technology in student-centered learning environments (TEME, $M = 2.10$, $SD = 0.77$). Hence, qualitative integration of technology seems to succeed on average in student-centered personalized learning settings, at least in this sample. Contrary to our assumption, students' voice and choice on the computer does not have a statistically significant impact on cognitive activation. A possible explanation could be that students' co-determination has a positive effect mainly on motivational aspects (Garn & Jolly, 2014; Walkington & Bernacki, 2018) and thus only an indirect influence on cognitive activation. Furthermore, the study does not analyze in which way students' voice and choice on the computer is made possible, nor whether it takes place on a very small scale, as is partly shown in studies on personalized learning (Gross et al., 2018; Schmid et al., 2022).

When it comes to supportive climate (RQ2), only students' voice and choice has a statistically significantly positive impact with small effect size ($B = .16$, $p \leq 0.01$). If teachers give the students more freedom to determine the what, when, and how of their technology-supported learning within the curricular requirements, students experience more learning support and a better assessment of their learning level by the teachers. This indicates an improved skill support but also a better learning support on a social-emotional level that can lead to better student outcomes (Cornelius-White, 2007; Freeman et al., 2014). However, contradictory to our second assumption, student-centered teaching methods supported by technology have no statistically significant effect on the supportive climate. This is a surprising result, but it could be related to the low frequency of student-centered teaching methods supported by technology as it is shown in the descriptive analysis (TEME, $M = 2.10$, $SD = 0.77$). Thus, it could be assumed that the use of technology in student-centered learning environments needs to exceed a certain threshold in order to produce measurable and statistically significant effects. For example, findings of international studies show in tendency higher effects on student skills in countries that are characterized by a high extent of technology use in class (Bos et al., 2014; Eickelmann et al., 2014).

In addition to the presented findings, certain limitations of the study should be mentioned. First, the independent variables of technology-supported personalized learning (TEME, VOCH) and the three dependent variables of instructional quality are based on student questionnaires and thus purely measured by self-reports, which is a method often criticized (Chan, 2009). However, a research and literature review based on studies of 50 years has shown that students' ratings of instructional quality can be applied reliably and validly in primary and higher education (Benton & Cashin, 2014; Fauth et al., 2014). The McDonald's Omega coefficients of the scales used confirm this with good values, except for the dimension of classroom management. Consequently, the results focusing on this subdimension (RQ3) are limited in their explanatory power. The reliabilities of cognitive activation (McDonald's $\omega = .64$) and supportive climate (McDonald's $\omega = .72$) could potentially be even improved by including more items in the short scales. This was not possible in the present study due to the comprehensive online-survey. The merely acceptable reliability of the student-centered teaching method might be explained by the fact that the implementations vary across schools and therefore students evaluate the questions differently (TEME, McDonald's $\omega = .68$). However, this always has to be taken into account when interpreting the results, especially in explorative studies. For the purpose of gaining insights into the instructional processes and quality of technology implementation that contribute statistically significantly to the interplay between technology-supported personalized learning and instructional quality, however, future research should seek to triangulate students' self-reports with video analysis rated by neutral observers for more detailed analysis (Pianta & Hamre, 2009).

Another point to consider is that our cross-sectional study lacks the data on standardized performance necessary for examining the development of student outcomes being impacted by technology-supported personalized learning approaches. However, the instructional quality is considered a pivotal and modifiable factor influencing student outcomes (Hattie, 2009). Thus, the examination of the instructional quality in a cross-sectional design constitutes a first step. In a second step, further longitudinal research studies should include performance tests and a larger sample to justice the multilevel structure that could contribute to a better understanding of the impact of technology-supported personalized learning on student outcomes.

Finally, it should be noted that the sample represents only a portion of innovative schools in Switzerland with their own understandings of technology-supported personalized learning, and the results are strongly influenced by the specific national education system.

Keeping these limitations in mind, the results of our study extend the current state of research that includes very limited studies examining technology-supported personalized learning in relation to instructional quality and student outcomes (Lee et al., 2021; Shemshack & Spector, 2020; Zhang et al., 2020). The few empirical studies that exist represent almost exclusively the English-speaking areas (Bingham et al., 2018; Gross et al., 2018; Underwood et al., 2007; Zhang et al., 2020). Thus, this exploratory study from Switzerland complements the fragmentary body of previous research by providing a first insight into the relationship between technology-supported personalized learning and instructional quality in the German-speaking context. Further, this explorative study takes up the challenge of examining the multidimensional approach *personalized learning* with no general accepted definition and sheds light on two dimensions of technology-supported personalized learning as a whole-school approach: (1) student-centered teaching methods and (2) students' voice and choice. In this way, the present study contributes to the existing body of research by adding further empirical findings of clearly defined dimensions of technology-supported personalized learning as a whole-school approach to the initially pre-dominantly theoretical discourse (Attwell, 2007; Bray & McClaskey, 2015; Keefe, 2007).

Conclusion

The schools of our sample indicate that student-centered teaching methods and students' voice and choice in technology-supported personalized learning have the potential to improve two dimensions of the instructional quality. Implementing student-centered teaching methods supported by technology in class can help to cognitively activate students. Further, if the teacher gives the students the freedom to co-determine the content, the procedure, and the temporal aspects of their learning processes supported by technology, the students might feel better supported individually, which can foster their learning motivation. The emergency remote teaching during the pandemic also clearly showed how important it is for the students to feel well supported. Current findings on school lockdowns indicate that certain students encountered insufficient learning support by the teachers (Kurtz, 2020). In particular, students with fewer self-regulation skills emerged from the pandemic with a loss of learning (Blaskó et al., 2021; Maldonado & De Witte, 2022). Therefore, it is important to build up the necessary self-regulation skills as well as digital skills in technology-supported personalized learning. In addition, the results of this study, such as the rather low frequency of student-centered teaching methods supported by technology, need to be followed up, especially in light of the fact that media and information technology have been given greater importance by the new curricula for primary and secondary education in Switzerland.

Declaration of interest statement

None of the authors have conflicts of interest to declare with regard to the research that is presented in this manuscript or its funding.

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Appendix

Survey Results From Student Questionnaires

Table A1. Student-centered teaching methods in computer-supported personalized learning [TEME] based on Schmid and Petko (2019).

How often are you doing the following classroom activities on the computer?	Median	Mean	*SD*
I work in the learning atelier on the computer.	2	2.32	1.05
I work on the computer with my weekly schedule, study plan, or daily schedule.	2	2.00	1.01
I work with tasks from a workshop on the computer.	2	1.98	0.93

Notes. $N = 860$; *SD* = standard deviation; scale: 1 = (almost) never, 2 = about once a month, 3 = once or twice a week, 4 = (almost) every day; McDonald's ω = .68.

Table A2. Students' voice and choice in computer-supported personalized learning [VOCH] based on Schmid and Petko (2019).

How often are you doing the following classroom activities on the computer?	Median	Mean	*SD*
I can decide how to proceed when learning on the computer.	3	2.97	0.91
I can manage my own time when learning on the computer.	3	2.91	0.95
I can decide for myself what I learn on the computer.	3	2.71	1.00

Notes. $N = 860$; *SD* = standard deviation; scale: 1 = (almost) never, 2 = about once a month, 3 = once or twice a week, 4 = (almost) every day; McDonald's ω = .82.

Table A3. Instructional quality [Iqual] adopted from Bos et al. (2011) and Fauth et al. (2014).

	Median	Mean	*SD*
Classroom management			
In class, everyone knows the rules that must be followed.	4	3.57	0.57
In class, it is clear what students are allowed to do and what students are not allowed to do.	4	3.53	0.67
In class, students fritter away a lot of study time.	3	2.72	0.69
Cognitive activation			
My teachers want me to be able to explain my answers.	3	3.16	0.73
My teachers give us tasks that seem to be difficult at a first glance.	3	3.32	0.65
My teachers give us tasks that I have to think about very thoroughly.	3	3.16	0.7
Supportive climate			
My teachers take time to explain things to me that I did not understand.	4	3.52	0.62
My teachers give me advices on how I can learn better.	3	3.35	0.68
My teachers know what I am already good at.	3	3.30	0.60
My teachers notice when I need support.	3	3.08	0.73

Notes. $N = 860$; *SD* = standard deviation; scale: 1 = totally disagree, 2 = somewhat disagree, 3 = somewhat agree, 4 = totally agree; McDonald's ω = .76.