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Young learners' motivation, self-regulation and performance in personalized learning

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ABSTRACT

Introduction: Personalized learning, a topic that has garnered significant attention in education, is known for its potential to cater to student's unique needs and improve educational outcomes. However, most large-scale longitudinal studies on personalized learning have primarily focused on middle school students and above (age $\geq$11). This study, in contrast, delves into the uncharted territory of how personalized learning affects younger students (ages 7–12), a domain largely overlooked by large-scale studies.

Objective: To understand the effect of PL on young learners' academic performance, metacognitive awareness, and motivation.

Method: Multidisciplinary design teams embedded personalized learning in eight participating elementary schools, resulting in personalized learning interventions tailored to each school in four subjects. The effects were measured over three years among 588 students and 82 teachers and analyzed using a Bayesian Gaussian regression with random intercept models and nested groups.

Results: We found significant evidence that the personalized learning interventions fostered academic performance in two of the four subjects: math and spelling. Regarding spelling, we found that the schools in which metacognitive skills were explicitly trained improved their students' spelling performance significantly compared to other schools. We found significant evidence suggesting that student ICT skills improved metacognitive awareness, intrinsic motivation, and math performance. We also found significant evidence that teachers' ICT skills support student metacognitive awareness. However, we could not confirm the theorized effect of personalized learning on metacognitive awareness or students' intrinsic motivation.

Conclusion: Our study provides evidence-based recommendations for implementing personalized learning interventions in elementary schools, particularly for math and spelling. Finally, improving ICT skills among students and teachers benefits students in math and in their metacognitive skills.

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1. Introduction

Personalized learning has gained considerable attention in education due to its potential to cater to the unique needs of students and improve educational outcomes. Personalized learning refers to instruction in which the pace of learning and the instructional approach are optimized for the needs of each student (Prain et al., 2018). Personalized learning activities are meaningful, relevant to students, driven by their interests, and often self-initiated. It aims to help students reach their maximum potential by customizing instruction. This includes adapting what is taught, how it is taught, and how it is learned to meet individual needs. These needs can be based on, for example, diverse student characteristics and interests (Miliband, 2006). Adapting the what and how of teaching and learning means that personalized learning is not a 'one-size-fits-all solution' but a promising approach that can transform education.

Studies that report on the effects of personalized learning in the short term have demonstrated the effectiveness of personalized learning in improving academic performance, metacognitive awareness, and motivation. By short-term, we mean studies that investigated the effects of personalized learning in a period shorter than four and a half months (Major et al., 2021). Recent systematic literature reviews by Bernacki et al., (2021) and Fariani, Junus, and Santoso (2023) found significant short-term positive effects on students' intrinsic motivation, metacognitive awareness, and academic outcomes. These studies suggest personalized learning can effectively engage students by catering to their interests and needs.

However, the literature reveals that long-term studies exploring the sustained impact of personalized learning are far less common. The scarcity of these studies limits our understanding of how personalized learning influences student outcomes over extended periods. Furthermore, the limited number of long-term studies on personalized learning that do exist have primarily focused on students aged 11 and above. For example, Pane et al. (2015) conducted a comprehensive three-year study across 31 schools, primarily involving middle school students. Major et al. (2021) also found that participants were at least 11 years old in their meta-analysis of ten long-term studies. Much like the literature reviews, these studies also have demonstrated positive outcomes in academic performance, metacognitive awareness, and motivation among older students.

Thus, there is a notable gap in the literature regarding the impact of personalized learning on younger students, specifically those aged 7 to 11 (elementary school age). There is a limited amount of literature reviews (Deunk et al., 2018) and experimental studies (Bang et al., 2023; Thai et al., 2022) focusing on the effects of personalized learning on younger students, but these focus only on short-term outcomes, neglecting both the long-term effects and the metacognitive and motivational components of personalized learning. This age group is crucial for study because metacognitive awareness and motivation are highly age-dependent. Younger children typically have lower metacognitive abilities, which affects their capacity to manage their learning independently (Flavell, 1979). This is important because metacognitive awareness explains a large portion (42%) of academic performance in elementary school (Carr et al., 1994; Özsoy, 2011). At the same time, they tend to have higher intrinsic motivation than older students, as motivation decreases systematically up to age 12 (Gillet et al., 2012). However, although older students have lower motivation, they benefit from the significant growth in metacognitive skills between the ages of 11 and 14 (Kuhn, 2000). Being older, they are better equipped to engage in self-directed learning, a core component of personalized learning. As age plays a significant role, it is essential to understand how personalized learning affects younger students.

Our study addresses this gap by exploring the effects of personalized learning on academic performance, metacognitive awareness, and motivation among elementary school students aged 7 to 11. This large-scale longitudinal study investigates how personalized learning interventions can be tailored to support younger students' development, providing valuable insights into its long-term benefits and challenges. This study aims to answer the following research question*: How does personalized learning affect young learners' academic performance, metacognitive awareness, and motivation?* We expect personalized learning to enhance young learners' intrinsic motivation, metacognitive awareness, and academic performance (Alamri et al., 2020; Deunk et al., 2018; Niemiec & Ryan, 2009; Smale-Jacobse et al., 2019).

In the next section, we explore the challenges of implementing personalized learning in elementary schools and the mechanisms behind its expected effects on academic performance, metacognitive awareness, and intrinsic motivation.

2. Theoretical background

A recent systematic review by Bernacki et al. (2021) stresses the context dependency of personalized learning. What works in a secondary school may not work in a primary school because students in primary school have different interests and needs compared to their middle school counterparts. Personalized learning accommodates these interests and needs by moving away from a one-size-fits-all approach to education (Hoic-Bozic et al., 2016; Xie et al., 2019). This allows diversity in learning preferences, approaches, and intellectual development (Felder & Brent, 2005). Personalized learning results in an instructional experience responsive to these features in ways that should (metacognitively and motivationally) engage the students and foster their academic performance (Bernacki et al., 2021). The review by (Fariani et al., 2023) confirms this by indicating that personalized learning research is slowly moving from academic performance as a sole success measure to embracing metacognitive awareness and intrinsic motivation as additional success measures. The following paragraphs explore the benefits of personalized learning from metacognitive awareness, intrinsic motivation, and academic performance perspectives.

2.1. The metacognitive awareness perspective

The term metacognition, coined by James H. Flavell (1979), originally described the concept of 'knowledge and cognition about cognitive phenomena' (p. 906). Its definition has since evolved to 'thinking about thinking.' Still, Flavel has also explained that

"Metacognition refers to an individual's knowledge of cognitive processes and output or his/her knowledge about anything related to them." Flavell emphasized that metacognition goes beyond comparing subjective versus objective cognitive performance, a distinction already explored in previous studies. Metacognition helps students learn, behave well, get along with others, and become independent (Moohr et al., 2021). Managing your learning is critical to metacognition and essential for implementing personalized learning and increasing student autonomy (Marquenie et al., 2014).

In the first issue of *Metacognition and Learning*, Veenman et al., 2006 noted that one term commonly associated with metacognition is Metacognitive awareness, meaning being aware of how you think. Metacognitive awareness is important in personalized learning because the locus of control shifts from teacher to student. This requires students to do more explicit goal-setting, planning, and evaluation of learning activities (Heereveld, 2020). Practicing these activities causes the student to develop more metacognitive awareness (being more mindful of what they are doing, why, and how) due to the increased autonomy provided by personalized learning (Sajna Jaleel, 2016).

The concept of metacognitive awareness has since been defined to consist of two components: knowledge of cognition and regulation of cognition (B. Kim et al., 2017; Ning, 2019; Sperling et al., 2002). Schraw & Dennisson's (1994) conception of these two component structures has been repeatedly verified using the Metacognitive Awareness Index, most recently by Alotaibi, 2024 and Moxon (2023). Metacognitive awareness allows students to plan, sequence, and monitor their learning, outperforming metacognitively unaware students (Schraw & Dennison, 1994).

The knowledge component includes declarative, procedural, and conditional knowledge of cognition. Declarative knowledge (*what is a bicycle?*) is descriptive and contains factual and conceptual knowledge (Alexander & Winne, 2006). Procedural knowledge (*how do I ride a bicycle?*) is know-how or practical knowledge (Saks et al., 2021). Conditional knowledge (*when should I ride a bicycle?*) involves metacognitive thinking, pondering when to apply declarative and procedural knowledge (Saks et al., 2021).

The regulation of cognition component refers to how well the student can regulate their learning. This means identifying their responsibilities (*task orientation*), setting their own goals (*planning* their homework), choosing and applying their learning strategies (doing and *monitoring* their homework), and reflecting on the process (*evaluating* their homework). Students with good metacognitive awareness can better follow a personalized learning process and choose better learning strategies (Kester et al., 2018). Improved metacognitive awareness can also improve performance (Devolder et al., 2012; Nota et al., 2004; Pintrich, 2000; Robson et al., 2020).

Metacognitive awareness is needed for personalized learning and vice versa (Habermehl et al., 2019). A recent systematic literature review of personalized learning by Fariani and colleagues (2023) concluded that the focus of personalized learning research could be expanded beyond its effect on academic performance to include the application of metacognitive awareness. Recent review studies by Bernacki et al. (2021), Zhang, Basham, and Yang (2020), and Fariani et al., (2023) confirm the effect of personalized learning on metacognitive awareness. However, the studies in these reviews target older learners, revealing a notable gap in long-term studies with primary school children. Studies into the effect of personalized learning on metacognitive awareness confirm its effect on secondary education (Ingkavara et al., 2022), undergraduate education (R. Kim et al., 2014; McQueen & Colegrave, 2022; Su, 2020), and adult education (Arroyo et al., 2014). However, none of these are long-term studies, nor do they research young learners. This emphasizes the need for longitudinal research to understand these effects in younger learners better because age is an important aspect of a student's capacity for metacognitive awareness and the ability to make informed choices about their learning process (Desoete et al., 2019; Reeve et al., 2003). From the age of 6 onwards, students learn to adjust the judgment of their performance noticeably more accurately with each semester (Desoete et al., 2019; Stolp & Zabrucky, 2009; Vanderswalmen et al., 2010).

2.2. *The intrinsic motivation perspective*

Intrinsic motivation refers to the student's goal-directed behavior that meets internal psychological needs (Kremen et al., 2016; Mayer & Estrella, 2014). We expect personalized learning to increase intrinsic motivation through two mechanisms. First, because the *control* of learning activities shifts from teacher to student, this increase in learner control is especially effective in increasing the intrinsic motivation of young learners (Eitam et al., 2013; Kuhl, 2000). Second, the increased learner control can also result in the student experiencing more *autonomy*, increasing intrinsic motivation because students are more motivated to learn something they choose (Habermehl et al., 2019). Setting their own goals and the freedom to choose are two aspects of autonomy that increase intrinsic motivation. Alamri et al., (2020) and Niemiec and Ryan (2009) have verified this process. Cordova and colleagues (1996) verified this mechanism in a long-term study. Intrinsic motivation and its components have been reliably measured in the academic subjects such as math (Monteiro et al., 2015), reading comprehension (Grolnick & Ryan, 1987), spelling and vocabulary (Monteiro et al., 2015), and ICT skills needed for personalized learning (Deci et al., 1994). The Intrinsic Motivation Index has repeatedly verified that intrinsic motivation is mainly measured by its core component: a student's *interest and enjoyment* (Plant & Ryan, 1985). How a student perceives her *choice* and *competence* are theorized to be positive predictors of self-report and behavioral measures of intrinsic motivation. How *valuable* and *useful* a student perceives her experiences is also a key influence on intrinsic motivation. Personalized learning intentionally encourages room for a student's motives (e.g., *the student is motivated by trains*). If learning as a result of these personalized motives is positively assessed (*successfully learning about momentum through the subject of trains*), students experience a "win," which leads to an increased desire or intrinsic motivation towards learning (Alamri et al., 2020; Cornelius-White, 2007; Gómez et al., 2014; Gutierrez et al., 2016; Pontual Falcão et al., 2018). The interaction between intrinsic motivation and personalized learning also works the other way around. Intrinsic motivation affects the student's learning choices (*a student who is motivated to learn about trains will be more invested in their learning strategy, learning processes, and performance outcomes if the outcome is learning more about trains*), making student intrinsic motivation critical for successful personalized learning (Lehmann et al., 2014; Moos & Bonde, 2016).

Intrinsic motivation significantly varies between primary and secondary school students. In primary school, children often engage in tasks for fun. They exhibit high levels of intrinsic motivation, driven by their natural curiosity, enthusiasm, and desire to explore the world (Gottfried, 1990). In contrast, secondary school students face increased academic pressures, diminishing their intrinsic motivation. This shift from a playful learning environment to one focused on academic achievement often leads to a decline in self-directed motivation (Eccles et al., 1993).

In addition to Fariani et al., (2023) and Zhang et al. (2020), a meta-analysis by Major et al., (2021) concludes that personalized learning increases learners' intrinsic motivation. However, Fiarini draws this conclusion only for higher education and stresses that research analysing the impact of personalized learning implementations on motivation is limited. Also, Major's conclusions regarding the effect of personalized learning on motivation are limited to students 11 years and older. Additionally, the long-term effect of personal learning on young learners' motivation remains unclear. None of the included studies focus on both long-term effects and young learners. This emphasizes the need for longitudinal research to better understand these effects in younger learners.

2.3. *The academic performance perspective*

Academic performance is the growth in cognitive knowledge usually determined by achieving course objectives and quantified through quizzes or exams (Yusuff, 2018). Identifying the factors that affect academic performance is one of the essential tasks of educational researchers and psychologists (Mega et al., 2014). Personalized learning has proven to foster academic performance in STEM, mathematics, and writing, especially with students traditionally considered unlikely to succeed or students who come from disadvantaged backgrounds (Clark & Kaw, 2020; Makhambetova et al., 2021; Prain et al., 2013; Schrader & Grassinger, 2021; Walkington, 2013). Personalized learning closes achievement gaps by adapting instructional methods and content to individual student needs and pacing, enhancing engagement and comprehension (Pane et al., 2015; Walkington, 2013).

However, while a substantial body of research supports the benefits of personalized learning on academic performance, most of these studies focus on older students. Long-term studies examining the sustained impact of personalized learning on academic performance are predominantly conducted with students aged 11 and above. For instance, Pane et al. (2015) conducted a comprehensive three-year study across 31 schools, primarily involving middle school students, and reported positive outcomes in academic performance. Similarly, Major et al. (2021) found that most participants in their meta-analysis of long-term studies were at least 11 years old, with consistent findings of improved academic performance. Again, the few available studies undertaken in primary schools tend to focus on short-term outcomes, neglecting the sustained effects on academic performance (Bang et al., 2023; Thai et al., 2022).

Research on personalized learning for younger students (ages 7–11) is limited, particularly in the context of long-term studies. This gap is critical, as younger students experience rapid growth in cognitive abilities and are motivated to develop these skills (Deunk et al., 2018; Gillet et al., 2012). Because early academic success strongly predicts future educational outcomes (Duncan et al., 2007), understanding how personalized learning affects younger students over an extended period is crucial.

2.4. *The role of ICT in personalized learning*

ICT is important in many personalized learning implementations, as it facilitates tailoring education to a student's needs. Therefore, the ICT skills of both students and teachers play a role in the effects of personalized learning. These effects go both ways: personalized learning environments (that integrate ICT) help students to develop ICT skills (Lai & Pratt, 2004; Slavin & Heritage, 2016; Zheng et al., 2016), but on the other hand the effect of personalized learning on student performance depends on teacher's ICT skills (Ertmer & Ottenbreit-Leftwich, 2010; Lawless & Pellegrino, 2007; Tondeur et al., 2012).

To reap the benefits of personalized learning, the school infrastructure and available technology should align with teachers' needs (Bingham et al., 2018). High teacher-student ratios make personalized learning only feasible with ICT (McCombs, 2008). Bernacki and colleagues's recent review found that more than 80% of personalized learning implementations required access to some form of learning technology. Subject-specific ICT (such as mobile math applications) are a powerful way to support academic performance in STEM, math, and writing (Clark & Kaw, 2020; Schrader & Grassinger, 2021; Walkington, 2013). Teachers experience high demands on their instrumental and professional ICT skills in personalized learning. Tondeur et al. (2012), Ertmer and Ottenbreit-Leftwich (2010), and Lawless and Pellegrino (2007) highlight the importance of this demand on teachers' ICT skills; they need the skill to integrate technology into personalized learning. For these reasons, we also measured teacher ICT skills in this study.

Although ICT is essential for the large-scale implementation of personalized learning, it must not take over student self-regulation (Bennett, 2011; Molenaar, 2021, 2022; Winne, 2018). ICT should let students regulate their learning process (Devolder et al., 2012; Marquenie et al., 2014; Vandewaetere et al., 2011). Students must develop the skills to perform tasks and solve problems using ICT (Fu, 2013; Martin & Grudziecki, 2006; Sarkar, 2012). According to Fu, these ICT skills are needed to use digital tools, educational applications, and digitally sourced information to support achieving goals in school and life. ICT skills are essential for personalized learning because the positive effects of subject-specific personalized learning are even more apparent when using ICT (Deunk et al., 2018; Maeng, 2017). Students in personalized learning environments integrating ICT tools develop essential ICT skills (Lai & Pratt, 2004; Slavin & Heritage, 2016; Zheng et al., 2016). Therefore, we measured student ICT skills in this study.

3. Present study

In sum, the positive effects of personalized learning on academic performance, metacognitive awareness, and intrinsic motivation have been established but are dependent on the student's development and the educational context. In this large-scale (multiple schools) longitudinal (three-year), we specifically focus on elementary students (ages 7–12). We expect personalized learning with ICT to improve students' intrinsic motivation, metacognitive awareness, and learning outcomes in math, spelling, reading comprehension, and vocabulary (Waldrip et al., 2016). We made the following predictions based on the theoretical background.

Hypothesis 1. Personalized learning improves intrinsic motivation (Cordova & Lepper, 1996; Niemiec & Ryan, 2009).

Hypothesis 2. Personalized learning improves metacognitive awareness (Arroyo et al., 2014).

Hypothesis 3. Personalized learning improves academic performance (Pane et al., 2015; Major, 2021).

Hypothesis 4. Student and teacher ICT skills improve the development of intrinsic motivation, metacognitive awareness, or academic performance (for students, see Lai & Pratt, 2004; Slavin & Heritage, 2016; Zheng et al., 2016) (for teachers, see Ertmer & Ottenbreit-Leftwich, 2010; Lawless & Pellegrino, 2007; Tondeur et al., 2012).

4. Method

This study uses a longitudinal, between-subjects, repeated measures design, allowing us to assess the change in variables or constructs over time.

4.1. Participants

Students and teachers from Grades 2 to 6 (Dutch 'group 4′ to 'group 8', ages 7 to 12) from eight Dutch schools for primary education participated in this study. The eight schools' Social Economic Status (SES-WOA) range covered 0 (from −0,144 to 0,251). This indicates they are of comparable SES to the average Dutch school. SES was accounted for because socioeconomic status significantly impacts ICT skills (Deursen & Van Dijk, 2014; Falck et al., 2021; Scherer & Siddiq, 2019). Parents were asked to give informed consent for their children to participate in the research.

Seven hundred twenty-one students completed the first intrinsic motivation and metacognitive awareness measurement. Five hundred eighty-eight students completed all three yearly measurements. Because the study ran for three years, students dropped out (they graduated from secondary education after Grade 6) and dropped in (graduate to Grade 2) of the experiment for natural reasons. In addition, the representation of participants varied per school and grade. Participants from School #3 formed the largest group (24.9% of our dataset), while participants from School #8 formed the smallest group (5.9% of our dataset). The oldest students (twelve-year-olds) were best represented (22% of our dataset), with a gradual decrease in participants to eight-year-olds represented the least (17% of the dataset).

Forty-one classes (52.3% of participants) were in the experimental condition over three years. These participants were labeled as the experimental condition for the specific year they received a personalized learning intervention.

Thirty-five classes of the participating schools did not implement interventions designed by the design teams. They received the established effective educational method normally given by the school and acted as active control groups (Au et al., 2020). These active control groups followed the regular curriculum and methodology but were also asked to fulfill the yearly measurement of intrinsic motivation and metacognitive awareness.

Eighty-two teachers from the same eight Dutch primary education schools participated in this study. The Grades 2 to 6 (Dutch 'groep 4′ to 'groep 8') teachers completed the first measurement of the monitor Learning and Teaching with ICT (Uerz & Kral, 2014).

Consent was obtained from all participants according to the HAN University of Applied Sciences procedures for informed consent.[1] Data from the HAN University of Applied Sciences was shared with the Open University of the Netherlands for analysis. To safeguard data management, all applicable guidelines of the Open University of the Netherlands were followed.[2]

After describing the participating schools, students, and teachers, we detail the measures used for metacognitive awareness, student intrinsic motivation, and *academic performance*.

4.2. Measures

The following paragraphs present the measures used to quantify metacognitive awareness, student intrinsic motivation, and academic performance.

4.2.1. Metacognitive awareness inventory

Metacognitive awareness was measured by the Meta-cognitive Awareness Inventory Junior (Jr.MAI). All constructs measured in this Junior version were tailored for primary education (Sperling et al., 2002). The Junior Metacognitive Awareness Inventory is a student self-report scale developed to correspond to a two-factor model (Knowledge and Regulation of Cognition). Exploratory and confirmatory factor analysis by Kim et al. (2017) and Ning (2019) support the two underlying factors corresponding to Knowledge and Regulation of Cognition. Recent studies by Ning (2019) and Sukarelawan et al., (2021) support the validity and reliability of the Jr. MAI for use with children. The Jr.Mai has good psychometric properties, shows a good fit, has no gender bias, achieves unidimensionality, properly defines the latent variables, and classifies persons and items (Sukarelawan et al., 2021). We translated the Jr.MAI

[1] More information on the HAN informed consent procedure can be found at this link.

[2] More information on the OUNL data management procedure is available at the following link.

into Dutch. The translated Jr.MAI was presented and discussed with peer-aged students to check the ecological validity.[3] The Jr.MAI was digitally presented to the students in a custom online environment. Descriptive statistics of the Jr.MAI showed varying means and standard deviations. Metacognitive awareness factor loadings ranged from 0.30 for information management to 0.58 for Evaluation. The results of a confirmatory factor analysis performed with lavaan (version 0.6–9) confirmed the significant validity of the Jr.MAI constructs ($p < .001$) and are presented in Table 1 (Rosseel et al., 2021).

4.2.2. Intrinsic motivation inventory

Intrinsic motivation was measured with the Intrinsic Motivational Inventory (IMI) (Ryan & Deci, 2000). The IMI is a multidimensional scale developed in support of the self-determination theory, a strongly validated theory stating that three innate needs moderate intrinsic motivation and regulation: autonomy, belonging, and competence (Deci & Ryan, 2004; Ryan, 1982).

The IMI has been shown to measure the intrinsic motivation of the different subjects for which personalized learning implementation was developed, such as math (Monteiro et al., 2015), reading comprehension (Grolnick & Ryan, 1987), spelling and vocabulary (Monteiro et al., 2015), and the ICT skills needed for personalized learning (Deci et al., 1994). Past work has also shown IMI subscales to have strong temporal (test-retest) reliability (Tsigilis & Theodosiou, 2003). The concepts of interest/enjoyment, perceived competence, value/usefulness, and perceived choice were used for our specific primary education application. We translated the IMI into Dutch for this study. The translated IMI was presented and discussed with peer-aged students to check ecological validity.[4] The IMI was digitally presented to the students in a custom online environment. Descriptive statistics of IMI showed varying means and standard deviations. Factor loadings for intrinsic motivational concepts confirmed that Interest/enjoyment (0.51) is the core concept. The results of a confirmatory factor analysis performed with lavaan (version 0.6–9) confirmed the significant validity of the IMI constructs ($p < .001$) and are presented in Table 2 (Rosseel et al., 2021)

4.2.3. Academic performance inventory

"Academic performance" was operationalized into Cito-test scores. These Cito-test scores provide academic performance measures for math, spelling, and reading comprehension. The Cito-test is a nationwide Dutch test (used by 85% of Dutch primary schools) that uses an independent, standardized academic achievement score test (van der Schans et al., 2016). The Cito test has two hundred multiple-choice questions (Cito, 2022). The language section of the Cito test consists of spelling, reading comprehension, verbs, vocabulary, and writing. Arithmetic/mathematic questions cover measurements, time, money, fractions, percentages, and ratios. Study skills questions involve the child's ability to process information from dictionaries, tables, graphs, schemes, maps, etc. Academic performance results were collected from the school's database in collaboration with the participating schools and with the participant's consent. The anonymized performance results span four years. The first year (2018) was collected as a baseline. The following three years (2019, 2020, and 2021) overlap with the three motivation and self-regulation measurements. School #8 did not provide the authors with performance data for any subject. Math, spelling, reading comprehension, and vocabulary data were received from all remaining consenting participants in all other schools.

4.2.4. Student ICT skills

The ICT skills students need to benefit from personalized learning using ICT were measured with a single measurement of student's Personalized Learning with ICT (ECC-ICT) test (Ackermans et al., 2023). In short, in the ECC-ICT, the ICT competencies needed for personalized learning are clustered into three indicators: collaborative, effective, and creative use of ICT for personalized learning.[5]

This ECC-ICT test shows excellent composite reliability for collaborative use of ICT ($\omega = 0.80$), effective use of ICT ($\omega = 0.82$), and creative use of ICT ($\omega = 0.64$).

4.2.5. Teacher ICT skills

Second, this study used a single measurement of the teacher's ICT competency needed to teach personalized using the monitor 'Learning and teaching with ICT' (Kurver et al., 2020). The monitor 'Learning and teaching with ICT' is a digital questionnaire covering teaching with ICT (pedagogical use of ICT) and teaching about ICT (training students for ICT-literate participation in society). The competencies needed for Learning and Teaching with ICT cover four different areas: proficiency in teaching with ICT, competencies to learn and innovate, teachers' own ICT literacy, and vision of education (Uerz & Kral, 2014). This test shows excellent reliability with an α between 0.72 and 0.85 (Kurver et al., 2020, 2023).

4.3. Instrumentation: design teams

We continue the method section with a short explanation of how we used the design team method to address the embedding of personalized learning in schools because this affects our research design, school-specific interventions, and participants. (Van Loon et al., 2021, p. 24). A previously developed and tested design team approach was followed in all schools (van Vijfeijken et al., 2015). This design team approach aims to design innovative ICT-rich learning arrangements. It combines the phases of design-based research with more creative design thinking elements and cross-organizational learning. The approach follows six design principles: 1) The

[3] A PDF printout of the final Jr.MAI (in Dutch) can be found at this OSF Link.
[4] A PDF printout of the final IMI (in Dutch) can be found at this OSF Link.
[5] A PDF printout of the final ECC-ICT test (in Dutch) can be found at this OSF link.

Table 1
Confirmatory Factor Analysis for Jr.MAI primary education translated into Dutch.

Indicator	Estimate	Std. Error	z-value	p	Lower	Upper
Declarative Knowledge	0.459	0.047	0.9759	<0.001	0.367	0.551
Conditional Knowledge	0.427	0.049	0.8749	<0.001	0.332	0.523
Procedural Knowledge	0.594	0.065	0.9112	<0.001	0.466	0.722
Planning	0.436	0.053	0.8159	<0.001	0.331	0.541
Monitoring	0.344	0.050	0.6914	<0.001	0.247	0.442
Information Management	0.297	0.069	0.4294	<0.001	0.162	0.433
Evaluation	0.578	0.061	0.9445	<0.001	0.458	0.698

Table 2
Confirmatory Factor Analysis for IMI for primary education translated into Dutch.

Indicator	Estimate	Std. Error	z-value	p	Lower	Upper
Interest/Enjoyment	0.514	0.075	0.6867	<0.001	0.367	0.661
Perceived Competence	0.357	0.065	0.5456	<0.001	0.229	0.485
Value/Usefulness	0.333	0.074	0.4510	<0.001	0.188	0.477
Perceived Choice	0.136	0.038	0.3578	<0.001	0.061	0.210

starting point is an educational practical question or dilemma of the teacher(s); 2) There is multidisciplinary and cross-organizational cooperation; 3) The working method is open-ended and concept-driven; 4) Design teams work evidence-informed and design-oriented; 5) Knowledge sharing takes place in all phases within and outside the school/organization; 6) There is a connection with the school context and organization.

The design teams in the current study comprised 6 to 10 members per school (teachers from the school, the school leader, an ICT specialist from the school, a researcher from HAN University, a trained design process supervisor from HAN University, and sometimes students from teacher education (bachelor or master). The role of process supervisor was fulfilled by teacher trainers from a Dutch teachers' college for primary education (PABO). The role of the researcher was to ensure that implementations were evidence-informed, to ask questions, to give input from existing knowledge, and to help gather and interpret data. According to van Vijfeijken et al., (2015), this variation of expertise and perspectives is essential for the development of new, innovative practices and the needed transformational learning but also to get an overview of all relevant factors in a school to properly embed personalized learning solutions in the primary process and the total organization of education.

Each design team's starting point was Prain and colleagues' (2018) definition of personalized learning. Several interventions (vision and ambition workshops and an earlier developed serious game around personalized learning) were organized in each school. The design teams then designed, tested, evaluated, and implemented a school-specific intervention fitting the school's specific ambitions. The design team's process lasted four years, and their approach resulted in the implementation of personalized learning interventions tailored to each school.

The design teams' process to embed personalized learning also meant that researchers supported the school's design teams with periodic research workshops, observations, and interviews to examine what their intervention required of the school's organization, ICT infrastructure, teachers, students, and parents.

Research workshops were based on the method of 'Organising personalized learning with ICT' (Loon, Neut, Kral, & Ries, 2020). They aimed to visualize the teams' initial situation and desired outcomes. Subsequently, they formulated design requirements and designed, tested, and evaluated interventions to progress from their initial situation to their desired outcome. Teams underwent multiple iterations of this process in four years to achieve their desired outcome.

Observations were used to observe how personalized learning takes shape in the relevant learning area. Researchers also made periodic observations to determine if additional workshops or interventions were needed.

Data about students' progress on specific learning goals were discussed and used to evaluate, adapt, or reshape the interventions. The design teams also discussed and used the data gathered on intrinsic motivation, metacognitive awareness, and students' skills.

Interviews with design teams were held to monitor and evaluate the process. For example, the text box below shows how school #5 embedded personalized learning to increase students' metacognitive awareness. Other schools' implementations and how these implementations targeted intrinsic motivation, metacognitive awareness, and academic performance can be viewed on this OSF link.[6]

4.4. Procedure

Three measurements were taken using questionnaires over three years (October 2019, October 2020, October 2021). The students completed the questionnaires using a custom online questionnaire application. Students were advised to set the application to full screen to ensure the test items were fully visible. The students were presented with a preparational instructional video before starting

[6] The detailed description of how every school participating in this study developed its personalized learning interventions can be downloaded at this OSF link.

the test. The test began with five warm-up test items about unrelated topics so that the student could get used to the question types. They filled in the questionnaires in the classroom without assistance from the teacher or peers. Students used a laptop, Chromebook, or PC and a Google Chrome-based browser provided by the school. Each test item included a loudspeaker button that could be clicked to play an audio file reading aloud the text in the question and the answer options. This button was included to facilitate students who had difficulty reading. For this reason, students were allowed to wear earbuds. The custom online application allowed the results to be communicated to the teachers through a dashboard.

4.5. Analysis

4.5.1. Multilevel modeling

Multilevel analysis is suited for this type of complex longitudinal research in educational practice because it accounts for students changing classes or missing data points that result from a student, for example, being sick, transferring schools, or opting out of the study. Bayesian Multilevel modeling uses Markov Chain Monte Carlo (MCMC) algorithms. Given its complexities, MCMC algorithms are a good solution for accurately estimating our dataset. In MCMC algorithms, the expected response of a student at a given time depends on the associated covariates and past outcomes (Zeger & Qaqish, 1988). We assumed our study's serial metacognitive awareness and intrinsic motivational measurements were likely dependent. Bayesian Multilevel modeling leads to better and more conservative estimates of our dataset (Bryk & Raudenbush, 1989).

The formula for multilevel modeling is a Bayesian Gaussian regression with Random Intercept Models and nested groups. The formula states we have non-linear (1) growth of the univariate outcome variables of intrinsic motivation, metacognitive awareness, or performance (2) with classes nested in schools (3). Variables we can assume may have an impact on the student's academic and behavioral characteristics (such as student and teacher ICT competency) were taken into account as variables (4) (Goldstein & Spiegelhalter, 1996). Because standard errors and standard deviation varied in our dataset, we assumed that the experimental conditions' intercept and effect varied across students (nested in classes (5) in the population in pursuit of accurate results. Time (6) is assumed to impact the maturation of young learners over three years and is needed to distinguish between the effect of the intervention and maturation. Finally, students were grouped per condition[7] (7). These variables created the following formula[8] (see Fig. 1).

We used BRMS v2.16.1 in RStudio build 461 with the probabilistic programming language Stan in the background (Bürkner, 2017; Carpenter et al., 2017). Before we ran the analysis and got the posterior distribution from which we could deduce the results, it was essential to imagine a reasonable distribution of these results (prior expectations). Third-grade teachers (a year before the experimental grades 4–8) gave us a single teacher score of intrinsic motivational and metacognitive awareness to use as priors. These priors were very informative, so we also ran our models with weak prior to check prior sensitivity. The length of the Markov Chains was set to 40.000 iterations to see if they reached a stable estimation of the posterior distribution (5.000 warmup iterations, 35.000 post-burn-in iterations) (Makowski et al., 2021). Results were not defined per school or grade because multi-collinearity is introduced when entire schools (or most of their grades) belong to the experiment condition. Depaoli and van de Schoot's (2017) 10-point checklist was followed to interpret our results confidently.

4.5.2. Model stability and accuracy

Posterior checks showed that the distributions had a good fit. A sensitivity analysis found that results remained almost identical (with relative deviation levels of less than 1%) when tested with different parameter settings. We conducted our experiment in the classroom under ecologically valid conditions, which inherently introduced uncertainty in our analysis. The measurements of concepts started in parallel with the interdisciplinary design team process, meaning partial or pilot interventions were also measured. Bayesian Regression Models analysis allowed us to quantify the effect of this uncertainty on the explained variance (bayes r2) using the rstantools package. v.2.1.1 (Gabry et al., 2022; Gelman et al., 2019). The variables in Fig. 2 enabled our analysis to account for 30–69% of the variance in the data. The variance for intrinsic motivational concepts measured by the IMI could be better explained (34–69%) than the variance for concepts of metacognitive awareness measured by the Jr. MAI (22–35%) found in Table 3. The explained variance varied between schools. School #8 showed higher (double in most cases) r2 for every concept and maintained that IMI could be better explained (77–96%) than the variance for concepts of metacognitive awareness measured by the Jr. MAI (57–93%).[9] This may be explained by the fact that school #8 offered the highest amount of personalized learning interventions. An explained variance above 60% is acceptable in educational science because many factors impact a student's performance in practical classroom conditions (Hair, 2014; Pett et al., 2003).

4.5.3. Hypothesis testing

We report if the existing effect was significant and how strong the effect was using the Bayes factor (Lee & Wagenmakers, 2014). Bayes factor ranges from anecdotal evidence for the hypothesis (*bf* 1–3), moderate (*bf* 3–10), strong (*bf* 10–30), very strong (*bf* 30–100) to extreme evidence for the hypothesis ($bf > 100$) (Lee & Wagenmakers, 2014). Bayes Factors were calculated using the BayestestR

[7] A student is grouped in a condition per year. This is based on the active intervention in their school, class, and year. For example, it is possible that a school only had an intervention in the 7th grade. A student is then only counted as part of the intervention group in 2018, the year he was in the 7th grade at that specific school.

[8] A script containing all BRMS formulas is available at this OSF link.

[9] More detailed information such as Est. Error and distribution or the R2 can be found at this OSF link.

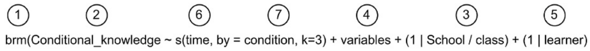

Fig. 1. BRMS formula example.

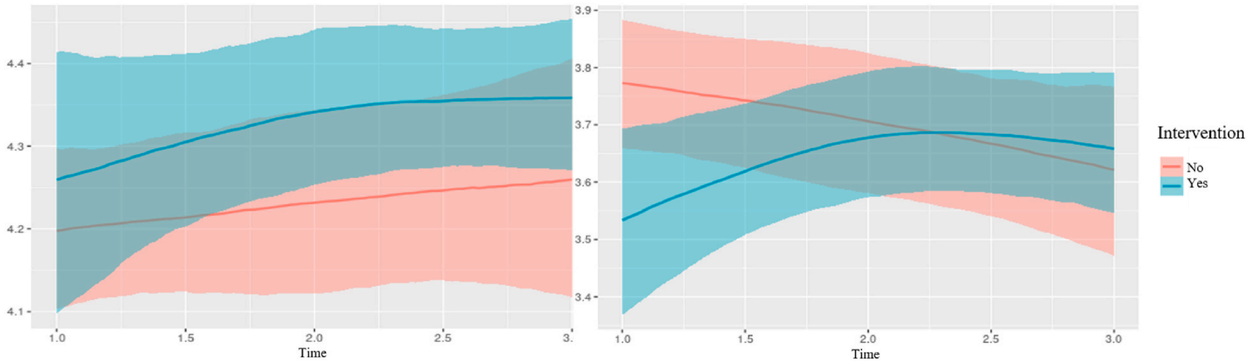

Fig. 2. The development of Value/Usefulness (left) and Perceived Competence (right) over time for the experimental condition (blue) vs the active control condition (red). (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)

Table 3
The average explained variance per the concept of intrinsic motivation and metacognitive awareness is expressed in Bayes R2. School #8 implemented the most applications, which may be reflected in the highest explained variance of all schools.

Concept	Bayes r2	Bayes r2 School #8
Interest/Enjoyment	0.687	0.81
Perceived Competence	0.609	0.81
Value/Usefulness	0.464	0.96
Perceived Choice	0.343	0.77
Declarative Knowledge	0.34	0.57
Conditional Knowledge	0.297	0.71
Procedural Knowledge	0.22	0.59
Planning	0.301	0.75
Monitoring	0.36	0.93
Information Management	0.301	0.67
Evaluation	0.353	64

package v0.11.5 (Makowski et al., 2021).

5. Results

The result section and Table 4 are designed to provide a summarised overview.[10]

Hypothesis 1. Personalized Learning Improves Intrinsic motivation

The effect of personalized learning on intrinsic motivation was insignificant. Bayes Factors in Table 4 display the results for this hypothesis (on the 1st row) “Hypothesis 1.” Fig. 2 illustrates the development of Value/Usefulness and Perceived Competence over time for the experimental condition (blue) vs. the active control condition (red). For a more detailed insight into which other variables affect the development of the students’ intrinsic motivation concepts, please see Table 4.[11]

Hypothesis 2. Personalized Learning Improves Metacognitive Awareness

The effect of personalized learning on metacognitive awareness was insignificant. Bayes factors displayed in Table 4 display the results for this hypothesis (on the 1st row) “Experimental.” Fig. 3 illustrates the development of Monitoring over time for the

[10] A script containing results in more detail, including smooths, TPE plots and describe_posterior tables with Median, 89% CI, pd, ROPE, % in ROPE, Rhat, ESS, and BF for every concept is available on OSF at this link.

[11] For a more detailed insight into which other variables significantly affect the development of the individuals’ concepts of intrinsic motivation, please see the textual summary at this OSF link.

Table 4

The variables in the columns (such as the experimental condition) and concepts predict the development of concepts in the rows. Bayes factors and their interpretation are indicated: anecdotal (A), moderate (M), strong (S), very strong (VS), and extreme (E).

	Intrinsic motivation				metacognitive awareness						
	Interest Enjoyment	Perceived Competence	Value Usefulness	Perceived Choice	Declarative Knowledge	Conditional Knowledge	Procedural Knowledge	Planning	Monitoring	Information Management	Evaluation
Hypothesis 1	0.017	0.06	0.093	0.017	0.017	0.021	0.032	0.038	0.097	0.044	0.032
Interest Enjoyment		>1000 (E)	>1000 (E)	>1000 (E)	0.229	0.010	0.029	5.48 (M)	0.230	2.06 (A)	140.28 (E)
Perceived Competence	>1000 (E)		0.17	0.008	432.98 (E)	1.40 (A)	0.031	0.021	0.023	0.017	0.022
Value Usefulness	>1000 (E)	8.75 (M)		0.026	0.482	0.138	0.021	0.015	0.764	0.011	0.023
Perceived Choice	>1000 (E)	0.008	0.037		0.184	0.012	0.026	0.031	0.017	0.016	0.020
Declarative Knowledge	0.051	15.51 (S)	3.58 (M)	0.269		>1000 (E)	13.52 (S)	3.19 (M)	0.013	0.185	0.856
Conditional Knowledge	0.009	5.37 (M)	0.534	0.007	>1000 (E)		1.91 (A)	0.109	0.043	0.014	26.88 (S)
Procedural Knowledge	0.016	0.008	0.014	0.010	7.93 (M)	1.49		0.110	0.119	0.414	0.053
Planning	5.27 (M)	0.017	0.006	0.009	0.933	0.055	0.151		8.88 (M)	6.25 (S)	29.43 (S)
Monitoring	0.133	0.007	0.061	0.008	0.007	0.068	0.272	8.70 (M)		438.77 (E)	>1000 (E)
Information Management	0.735	0.008	0.008	0.009	0.098	0.010	0.544	23.03 (S)	112.90 (E)		0.294
Evaluation	7.58	0.005	0.006	0.005	0.283	18.83 (S)	0.071	111.66 (E)	>1000 (E)	0.127	
ICT literacy instrumental	0.046	0.048	0.046	0.205	0.038	3.61 (M)	0.088	0.223	0.183	0.298	0.071
ICT literacy media	0.022	0.023	0.020	0.093	0.021	4.43 (M)	0.069	0.052	0.041	0.116	0.036
Student directed	0.053	0.046	0.488	0.027	0.033	0.110	0.120	0.062	0.070	0.562	0.063
metacognition	0.023	0.031	0.036	0.051	0.027	0.032	0.053	0.041	0.116	0.048	0.042
competency	0.046	0.044	0.043	0.031	0.084	0.043	0.073	0.181	0.276	0.128	0.058
didactic lesson	0.061	0.119	0.051	0.207	0.057	0.057	0.204	0.108	0.066	0.075	0.087
didactic dif. Basic	0.022	0.04	0.029	0.040	0.026	0.025	0.076	0.076	0.078	0.030	0.127
didactic. Advanced	0.029	0.03	0.124	0.034	0.037	0.035	0.085	0.058	0.057	0.095	0.149
Collaborative	0.006	0.011	0.040	2.94 (A)	0.005	0.005	0.007	0.012	0.007	0.006	0.010
Creative	0.007	0.091	0.006	0.010	0.008	0.009	0.009	0.011	0.012	0.015	0.015
Effective	0.006	0.155	0.007	0.006	1.11 (A)	0.008	0.011	0.010	0.009	0.007	11.62 (S)

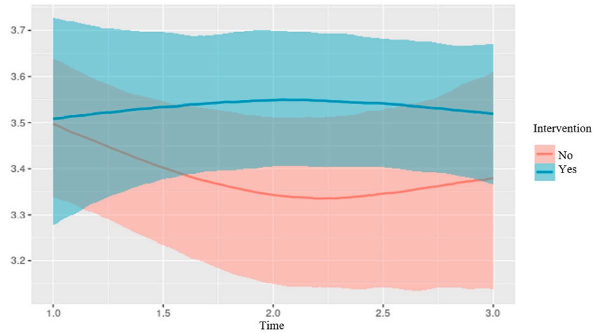

Fig. 3. The development of Monitoring over time for the experimental condition (blue) vs the active control condition (red). (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)

experimental condition (blue) vs. the active control condition (red). For a more detailed insight into which other variables affect the development of intrinsic motivation concepts, please see Table 4.[12]

Hypothesis 3. Personalized Learning Improves Academic Performance

The effect of personalized learning on performance was significant. The experimental condition showed extreme evidence for math (bf 322.29) and spelling (bf 109) (see Table 5). There was no evidence of an effect of personalized learning on reading comprehension or vocabulary. Further examination of the extreme evidence for math and spelling showed a significant difference between schools. School #5 showed a significant (bf 19.8) spelling effect over the other schools. School #5 implemented a 14-week metacognition-focused curriculum.

Hypothesis 4. Student and Teacher ICT Skills Improve Intrinsic Motivation, Metacognitive Awareness, or Academic Performance

Regarding student ICT skills, effective use of ICT had an anecdotal effect (bf 1.11) on metacognitive awareness(declarative knowledge), a strong effect (bf 11.62) on metacognitive awareness (evaluation), and an extreme effect on Math (bf 224.52). Collaborative use of ICT had an anecdotal impact (bf 2.96) on intrinsic motivation (perceived choice) and a moderate effect on Math (bf 7.27). Regarding teacher ICT skills, two out of the eight test constructs significantly affected student metacognitive awareness when tested using the Bayes Factor. ICT literacy instrumental skills (bf 3.61) and ICT literacy media skills (bf 4.43) had a moderate effect on metacognitive awareness (conditional knowledge).

6. Discussion

In this large-scale (multiple schools) longitudinal (three-year) study into personalized learning on an elementary school level, we expected personalized learning with ICT to improve elementary students' intrinsic motivation (H1), metacognitive awareness (H2), and learning outcomes (H3). In general, personalized learning has positive effects on directly targeted concepts (such as metacognitive awareness, math, and spelling). Improved ICT skills (H4) among students and teachers benefited from personalized learning (in math and metacognition). The results are discussed in depth in the following paragraphs.

Hypothesis 1. Based on research with older students, we expected

Personalized learning enhances intrinsic motivation due to increased autonomy, competence, interest, engagement, and learning effectiveness (Cordova & Lepper, 1996; Niemiec & Ryan, 2009). This expectation was supported by meta-analysis and review studies showing significant increases in intrinsic motivation in older students through personalized learning interventions ((Bernacki et al., 2021; Fariani et al., 2023; Major et al., 2021). Based on short-term studies, we expected similar positive effects on intrinsic motivation among younger students. Previous research has demonstrated that personalized learning can foster intrinsic motivation in short-term settings (Alamri et al., 2020).

Because our instrument for measuring intrinsic motivation worked well (the explained variance for intrinsic motivation was acceptable, and the explained variance for interest/enjoyment was exceptionally high), we can confidently say that we did not find evidence of the theorized effects of personalized learning on intrinsic motivation. We see three possible explanations for this outcome.

First, young students are often highly motivated (Gillet et al., 2012). Personalized learning does not affect students who are already highly motivated (Huang et al., 2023). The rationale is that highly motivated students do not need personalized learning paths.

Second, this study took place during the COVID lockdowns. These lockdowns hurt student motivation and metacognitive awareness, specifically regarding need satisfaction, well-being, and intrinsic motivation (Samsen-Bronsveld et al., 2023). The lockdowns turned student homes into learning environments, which, depending on the quality of the learning environment, impacted their stress,

[12] For a more detailed insight into which other variables influence the development of the individuals' intrinsic motivation concepts, please see the textual summary at this OSF link.

Table 5
Results for the bayes factor for math (H3a), spelling (H3b), and reading comprehension (H3c). Extreme (E) Bayes Factor evidence is indicated.

	Math (H3a)	Spelling (H3b)	Reading comprehension (H3c)	Vocabulary (H3d)
Bayes Factor				
Active control	<0.001	<0.001	<0.001	<0.001
Intervention	322.29 (E)	109.00 (E)	<0.001	<0.001

well-being, and motivation (Brachtl et al., 2023). This decline in motivation and metacognitive awareness because of the lockdowns may have negated the effect of this study.

Third, intrinsic motivation and metacognitive awareness must be explicitly targeted (Järvelä et al., 2021). However, the design teams did not implement an intervention directly targeting motivation. This may be a reason why intrinsic motivation was not affected.

Hypothesis 2. Based on research with older students, we expected Personalized learning to improve metacognitive awareness, as studies involving older students have shown positive effects on metacognitive skills (Ingkavara et al., 2022; R. Kim et al., 2014). Based on short-term studies, we expected enhanced metacognitive awareness among younger students through Personalized Learning interventions (Arroyo et al., 2014).

However, we did not find the expected effect of personalized learning on metacognitive awareness. We see two possible explanations.

First, the rapid development of young students' metacognitive awareness may have been stronger than the effect of personalized learning (Chen et al., 2022). Thus, children's metacognitive awareness in both groups may have improved significantly. Thus, a group difference was not found. This explanation is supported by the low explained variance (22–35%) we found, which raises the question of whether an unexpected variable (rapid metacognitive development) influenced the study. This rapid development is particularly visible in our data regarding declarative knowledge, where we see strong growth from both groups throughout our study.

Second, this aligns with Molenaar's (2021, 2022) work arguing against the effect of ICT on metacognitive awareness. It states that even the most sophisticated ICT (several of the ICT applications used in this study are specifically mentioned in Molenaar's work) fail to support metacognitive awareness due to most ICT taking over (offloading) regulation from students to the adaptive learning technology (Molenaar, 2021, 2022).

Hypothesis 3. Based on research with older students, we expected Personalized Learning to significantly enhance academic performance, supported by a meta-analysis of long-term studies showing positive outcomes in older students (Major et al., 2021; Pane et al., 2015). Based on short-term studies, we expected improved academic performance in younger students through personalized learning interventions.

Our intervention confirmed these effects and significantly affected students' spelling and math performance. Young children in early elementary school still acquire foundational literacy and numeracy skills, which may have made them responsive to personalized learning interventions. Because of these positive results, we examined how individual schools varied academic performance. School #5 showed a significant (bf 19.8) effect over the other schools' spelling. School #5 was also the only school that explicitly taught a 14-week metacognition-focused curriculum with two weeks dedicated to metacognition skills. A possible explanation is that the training in metacognition provided the students with the skills needed to regulate their personalized learning and improve spelling.

Hypothesis 4. Based on research with older students, we expected students' and teachers' ICT skills to significantly enhance Personalized Learning outcomes, as digital literacy is crucial in maximizing the benefits of Personalized Learning in older students (Fu, 2013; Martin & Grudziecki, 2006; Sarkar, 2012). Based on Zheng et al., (2016) meta-analysis of short-term studies, we expected positive associations between ICT skills and academic performance, metacognitive awareness, and motivation among younger students.

Results of student and teacher ICT skills confirm that students' ICT skills are important for personalized learning (Fu, 2013; Martin & Grudziecki, 2006; Sarkar, 2012). We found that a student's (collaborative and effective) ICT skills significantly contribute to their intrinsic motivation (perceived choice), metacognitive awareness (declarative knowledge and evaluation), and academic performance (Math). A recent study by (Sze Ming Loh et al., 2023) confirmed that students' ICT skills improve their math performance in countries with higher levels of ICT access.

However, we did not find this effect for our other subjects (spelling, reading comprehension, vocabulary) as Pagani et al. (2016) did. A possible reason may be that the effect of ICT skills is lower for students with high academic performance, family background, and general education (Pagani et al., 2016). Teachers' instrumental and media literacy also contributed to developing students' knowledge of using specific knowledge and skills (metacognition conditional knowledge). This transfer from teacher to student aligns with a study by Lorenz et al. (2019), who found that teachers' ICT skills are significant predictors for fostering the student's ICT skills. COVID may have positively affected Teacher ICT skills because teachers' motivation to use digital technologies in their teaching practice increased during COVID lockdowns. Especially their confidence in using technology for preparing lessons, class teaching, assessing and providing feedback, and communication (Beardsley et al., 2021).

6.1. Limitations

There are certain limitations to this study. First, all schools were supported by their design teams in having independent development timelines to introduce varying implementations in their chosen grades. Independent development timeline variations measured intrinsic motivation and metacognitive awareness during the design (no implementation), partial implementation, or piloting phase. To clarify these varying levels of implementation, the design teams were asked to report when an intervention took place post-hoc. Another limitation due to the varying implementations is the lack of logging of the tasks' load, frequency, and duration. Schools were neither expected nor technically capable of logging their implementations' load, frequency, or duration.

Second, the three-year time span of our research fully overlapped with COVID induced lock-downs and homeschooling (March 2020–June 2021), which may have negatively impacted the intrinsic motivation and metacognitive awareness of students (Holzer et al., 2021; Hornstra et al., 2022). Schools understandably focussed their effort on Emergency Remote Teaching, which may have impacted the speed and scale of the final personalized learning interventions.

Third, the priors for our multilevel analysis are based on teacher-reported student intrinsic motivation and metacognitive awareness. Teacher reporting bias can result from unconscious stereotyping and often influences racial/ethnic students. Teacher reporting risks bias through the teachers' explicit beliefs (DeCuir-Gunby & Bindra, 2022).

Fourth, a Think-Aloud process could have improved the reliability of self-report measures (specifically the jr.MAI) (Rovers et al., 2019). This would also have meant training students on the think-aloud technique (Eccles & Arsal, 2017). Because training students on thinking aloud improves their metacognitive awareness (specifically reflection), all participants must be trained to keep the conditions equal (Ahmad Khurram et al., 2022). Our practical argument for self-report measures (Jr.MAI, IMI) is that the seven hundred twenty-one students are measured yearly, creating a considerable workload of approximately 2000 questionnaires.

7. Conclusion

From a theoretical perspective, our study adds to the body of knowledge of longitudinal, multi-school research into personalized learning effects on elementary students. Our study contributes to the literature by following Fariani et al. (2023) systematic review advice and expanding research on personalized learning from its impact on academic performance into intrinsic motivation and metacognitive awareness. However, our results suggest that personalized learning interventions may not improve intrinsic motivation and metacognitive awareness. Our study contributes to understanding how the theorized effect of personalized learning on intrinsic motivation and metacognitive awareness translates to practice. We also nuance the assumption that even the most sophisticated ICT fails to support metacognitive awareness (Molenaar, 2022). Our findings suggest that student ICT skills (prerequisite for using ICT) can impact metacognitive awareness (Deunk et al., 2018; Maeng, 2017). Molenaar contributes this failure of ICT to the need for mechanisms in current ICT to gradually onload self-regulation from adaptive learning technology to the students. Our findings suggest that the student's ICT skills may also be a factor in this process.

From a practical perspective, subject-specific (math or spelling) personalized learning supported with ICT is recommended to teachers, educators, and policymakers. Specifically, our findings suggest that personalized learning interventions should be tailored to the unique needs of individual schools and that technology can be used to support personalized learning. Additionally, our findings highlight the importance of improving ICT skills among students and teachers to facilitate personalized learning benefits in math and metacognitive awareness. By doing so, educators can better meet the diverse needs of their students and promote academic success. Also, the practical benefit of implementing a curriculum focused on practicing metacognitive awareness techniques curriculum is underlined by school #5. This supports the assumption made by Järvelä et al. (2021), stating that intrinsic motivation and metacognitive awareness need to be explicitly targeted instead of expecting intrinsic motivation or metacognitive awareness to be affected by implementing ICT. The educational implication of this conclusion is that teachers should expressly teach metacognitive skills and should not rely on metacognitive awareness to develop as a side product of shifting regulation to the student.

Overall, our study provides important insights into the potential benefits of personalized learning and highlights the need for continued research into the best practices for implementing and supporting personalized learning interventions in schools.

CRediT authorship contribution statement

Kevin Ackermans: Writing – review & editing, Writing – original draft, Validation, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Marjoke Bakker:** Writing – original draft, Investigation, Data curation. **Anne-Marieke van Loon:** Writing – review & editing, Writing – original draft, Project administration, Methodology, Investigation, Funding acquisition, Conceptualization. **Marijke Kral:** Writing – original draft, Software, Resources, Project administration, Methodology, Investigation, Funding acquisition, Conceptualization. **Gino Camp:** Writing – review & editing, Writing – original draft, Methodology, Funding acquisition, Conceptualization.

Author note

We have no known conflict of interest to disclose.

Ethics

Consent was obtained from all participants according to the HAN University of Applied Sciences procedures for informed consent[13]. Data from the HAN University of Applied Sciences was shared with the Open University of the Netherlands for analysis. All applicable guidelines of the Open University of the Netherlands were followed to safeguard data management.[14]

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Declaration of competing interest

The authors have no conflict of interest to declare.

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Data availability

The datasets generated or analyzed during the current study are available in the Open Science Framework repository under https://osf.io/5ecrf/.

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[13] More information on the HAN informed consent procedure can be found at this link.

[14] More information on the OUNL data management procedure is available at the following link.

[15] More information on the iXperium Onderzoekswerkplaats Gepersonaliseerd leren met ICT-project can be found under this link.

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