Exploring the Perception of AI in Learning: Unveiling the Role of Student and Teacher Motivation and Self-Efficacy

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Abstract

Purpose. Artificial intelligence (AI) has a significant impact on education, but little is known about how primary and lower secondary school students perceive AI in learning. This study aims to explore both student and teacher motivation and self-efficacy in relation to students' perceptions of AI in learning.

Design/methodology/approach. Data from 907 primary and lower secondary school students and 53 corresponding class teachers from German speaking Switzerland was collected through questionnaires. Analysis was conducted using doubly multilevel structural equation modeling (ML-SEM).

Findings. Analysis revealed that students' motivation to learn with digital media is significantly linked to their perception of AI at the individual level. Furthermore, students' self-efficacy plays a crucial role for their motivation, with girls exhibiting lower self-efficacy to learn with digital media compared to boys. At the class level, teacher motivation to integrate digital media in teaching was significantly positively associated with student motivation.

Originality. This study is among the first to investigate primary and lower secondary school students' perceptions of AI. It distinguishes itself by considering both student and teacher variables in a ML-SEM.

Practical Implications. The research highlights the importance of fostering students' self-efficacy and motivation to learn with digital media, particularly among female students. Additionally, it emphasizes the need for a supportive and motivating teacher-student dynamic to create a more positive perception of AI in learning. These findings provide valuable insights for integrating AI in primary and lower secondary school settings.

Keywords: Artificial intelligence, K-12 AI education, Primary education, Secondary education

Article Classification. Research Paper

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Introduction

As artificial intelligence (AI) is changing the world it has also an impact on education that should not be underestimated. Some scholars even refer to it as a revolution (Seldon, 2020; Roll and Wylie, 2016). To get an overview about the current state of research regarding AI in education we considered systematic reviews. Examining recent systematic reviews (Zhou *et al.*, 2020; Zawacki-Richter *et al.*, 2019; Rizvi *et al.*, 2023; Crompton *et al.*, 2022) reveals that research on AI in education focusing on the lower levels is still in its infancy. For instance, Zhou *et al.* (2020) included in their systematic review of K-12 AI and education literature only 11 studies situated at the primary level and 13 examining AI education programs in middle schools. Especially at a young age, children should be taught the basic AI concepts in order to develop AI literacy (Kandlhofer *et al.*, 2016; Heintz, 2021). Long and Magerko (2020) highlighted the need for more research on students` perceptions of AI toward fostering AI literacy among children. Ottenbreit-Leftwich *et al.* (2023) captured through interviews existing ideas of students between the age of 9 and 11 concerning AI. Among the identified AI themes, there was one where students recognized that AI could improve our lives. However, research on factors influencing students` perceptions of AI as a learning tool is missing. Hence, in this study we are exploring different factors in students` perception of AI in learning on the lower educational levels by specifically investigating student and teacher variables. According to Marx *et al.* (2023), studies investigating perception in the context of AI insufficiently defined the term perception. Consequently, in the current study we provide a precise definition, interpreting perception of AI in learning as the perceived helpfulness for the student (i.e., learning process and practicability) along with the intention to use AI in learning.

Factors that can Play a Role for Students' Perception of AI in Learning

In the following section, our first point of focus is on student variables and how they may contribute to shaping their perception of AI in learning. Next, we will highlight the role of the teacher.

Student variables: The role of the student

To begin, we will take a look at motivational aspects. Motivation, in essence, involves the guiding of actions, thoughts, and emotions towards both conscious and subconscious objectives. It serves the purpose of initiating and sustaining behavior, as articulated by various scholars (Brophy, 2004; Götz, 2011; Linnenbrink-Garcia *et al.*, 2016). In the school context research suggests that it arises from the interplay between individuals within the social environment of the classroom and school (Urdan and Schoenfelder, 2006) and it is considered a fundamental education variable as it is a critical component of learning (Andermann and Dawson, 2011; Cavas, 2011; Murayama *et al.*, 2013).

In motivational psychology, motivation is commonly categorized into 'intrinsic motivation' and 'extrinsic motivation,' as outlined in self-determination theory by Ryan and Deci (2000). In the current study, we focus on students' intrinsic motivation (i.e., the motivation caused by the curiosity and joy of learning, rather than by external incentives, pressures or reward, Ryan and Deci, 2000; Ryan and Deci, 2020), and more specifically on their motivation to learn with digital media, as we expect, that this kind of motivation might be especially relevant for students' perception of AI in learning. Various factors are associated with students' motivation for learning (Yilmaz *et al.*, 2017), with self-efficacy being a major aspect.

Self-efficacy is a comprehensive concept which goes back to Bandura (1977) and generally refers to an individual's belief in their ability to succeed in a specific domain (e.g., mathematics) or in a specific task (e.g., computer self-efficacy: Marakas *et al.*, 1998) and it is important for motivation (Bandura, 2003; Bong and Skaalvik, 2003). Individuals who hold the belief that they are competent and capable of performing well in an activity are more likely to invest effort in that endeavor, as suggested by Bandura in 1977.

Digital media self-efficacy draws upon Bandura's concept and can be described as the degree to which a person believes they can proficiently operate digital media (Ulfert-Blank and Schmidt, 2022). It is a prerequisite for digital media skills and the effective use of digital media and is substantially shaped by prior experiences using digital devices (i.e., successfully or unsuccessfully; Marakas *et al.*, 1998).

In relation to students' perceptions and use of digital media, research by Aesaert and van Braak (2014) indicates that students' confidence in their information and communication technology (ICT) abilities is positively correlated with their internet and computer performance, as well as their motivation to engage with technology. In addition, Meelissen and Drent (2008) found that students' self-efficacy in computer use was positively associated with their computer attitudes including enjoyment and utility perceptions.

When it comes to students' self-efficacy to learn with digital media, it was found that students with high self-efficacy in using the internet exhibit superior information-searching strategies and performance in web-based learning tasks compared to students with low internet self-efficacy. In contrast to college students with high internet self-efficacy, those with low self-efficacy in this context lack the confidence to experiment with new methods for seeking information and solving problems on the internet (Tsai and Tsai, 2003). Chen (2017) found that students' computer self-efficacy contributes to their learning engagement and, in turn, their learning performance. Also, Tzeng (2009) noted that a students' belief about their abilities related to the use of technologies is a critical factor in determining the level at which they will engage in learning environments that are technologically integrated.

There is only little research that investigated self-efficacy and the perception of AI so far. Chai *et al.* (2021) found that self-efficacy was the most important factor that directly predicted students' behavioral intention, AI readiness (i.e., perceived level of comfort with the use of AI technology in every day live), and perceptions about the use of AI for social good (i.e., the use of AI to solve problems and improve people's lives). Furthermore, perceptions of learning AI for social good significantly predicted students' readiness to learn AI and intention to learn AI.

Since demographic differences in the development of students' motivational profiles and a corresponding need for different supports are noted in several studies (K. Ann Renninger *et al.*, 2018), we also want to consider students' age as an influencing factor for their perception of AI in learning. In detail, studies found a significant linear decrease in intrinsic motivation from 3rd grade through 8th (Gottfried *et al.*, 2001; Lepper *et al.*, 2005; Karumbaiah *et al.*, 2022).

Similarly, gender has been shown to influence the relationship between students' motivation and the topic or context of the learning task (Hoffmann and Haussler, 1998). When looking at digital media, meta-analytic findings indicate that boys reported higher level of ICT self-efficacy and interest compared to girls (Cai *et al.*, 2017; Whitley, 1997; Yu and Hu, 2022). Regarding the perception of computers Meelissen and Drent (2008) found general positive attitudes toward computers in grade 5, but boys were even more positive than girls. They also found in their multilevel model that it seems that the class 'matters' more for girls' computer attitude than for boys' computer attitude (i.e., more variance explained for girls at the class level).

Teacher variables: The role of the teacher

Besides the students themselves, we expect that teachers can play a significant, albeit indirect, role in influencing students' perception of AI in learning - especially the class teacher, since this is the teacher, the students spend most of their classroom time with. Studies have established a connection between teacher motivation and student motivation (Atkinson, 2000; Roth, 2014; Ryan and Deci, 2016; Woolfolk Hoy, 2021), which, in turn, as state above can be expected to impact students' perception of AI in learning. Additionally, teacher self-efficacy, particularly in the context of digital media, may be important for shaping student motivation and consequently their perception of AI in learning. We will describe this rational in detail in the following paragraphs.

Teacher motivation encompasses the driving factors that lead teachers to engage in teaching and enhance the quality of their work (Richardson *et al.*, 2014; Pelletier and Rocchi, 2016; Collie and Martin, 2017). Specifically, teachers' intrinsic motivation for teaching reflects their innate drive to focus on the teaching process, continually promote their professional development, and sustain their interest and attention on teaching (Liu *et al.*, 2019).

Empirical evidence supports our idea that teacher motivation can exert a positive influence on student motivation for learning (Atkinson, 2000; Roth, 2014; Ryan and Deci, 2016; Woolfolk Hoy, 2021). In detail, students tend to be more inclined to explore new skills and engage in deeper learning when they perceive their teachers as intrinsically motivated to teach (Radel *et al.*, 2010; Wild *et al.*, 1992).

Pedagogical and psychological theories suggest that the relationship between teachers' intrinsic motivation for teaching and students' intrinsic motivation for learning is complex, with various internal mechanisms at play (Ahn *et al.*, 2021). Teachers' motivation can not only directly influence students' motivation but also enhance their intrinsic motivation by fostering teaching practices that support autonomy, competence, and relatedness, fulfilling students' basic psychological needs (Kalyar *et al.*, 2018; Zou *et al.*, 2023). In essence, motivated teachers can serve as role models, inspiring students to engage more deeply in their studies and arousing enthusiasm, especially in areas like technology. Moreover, motivated teachers are more likely to create dynamic and engaging lessons, capturing students' interest and making the learning experience enjoyable. This, in turn, can lead to higher levels of student motivation and active participation in the educational process.

In addition to teacher motivation, teacher self-efficacy plays a pivotal role. Self-efficacy refers to teachers' beliefs of their ability to excel in their work and is closely linked to instructional quality and teacher effectiveness (Holzberger *et al.*, 2013; Künsting *et al.*, 2016; Karumbaiah *et al.*, 2022; meta analysis by Klassen and Tze, 2014; Tschannen-Moran *et al.*, 1998). Ertmer (1999) and Ertmer and Ottenbreit-Leftwich (2010), reiterate in their work that self-belief, confidence, ability to make connections and see relevance are crucial for teachers in the success of integrating digital media into their teaching.

Teacher self-efficacy beliefs are also considered to significantly shape student motivation in learning and achievement (Rodríguez *et al.*, 2014). For instance, Daumiller *et al.* (2021) highlighted the influence of teacher self-efficacy beliefs on student outcomes in higher education (i.e., positive association with student's overall rating of the course, learning and positive emotional experiences) and Thoonen *et al.* (2011) found associations between teacher self-efficacy and student motivation to learn in primary school.

Regarding the use of AI, research is scarce. However, initial findings indicate that teachers who are capable of using AI for teaching can enhance their teaching effectiveness and positively influence student motivation and self-efficacy for learning (Ng *et al.*, 2023; Seo *et al.*, 2021; Guerrero-Roldán *et al.*, 2021; Vazhayil *et al.*, 2019).

Overall, from these findings it can be expected that the involvement of teachers, driven by the motivation to integrate digital media in teaching and supported by self-efficacy to integrate digital media in teaching, can contribute significantly to shaping students' perception of AI by influencing their motivation to learn with digital media in the learning process.

The role of other variables

We are aware, that next to the students themselves and the teachers, also other variables could be relevant in this context and might shape the students' perception of AI in learning. Especially the parents might play an important role, too. Liu and Chiang (2019), for example found that both family background and student-teacher interactions are related to students' learning motivation. Parents may also have a pivotal role in shaping students' beliefs towards digital media which are in turn an important precursor to students' use of digital media for learning (Hammer *et al.*, 2021). Meelissen and Drent (2008) found that the extent to which students experience encouragement by their parents to use and learn about computers is an important factor with regard to the computer attitudes of students. In terms of AI, Druga *et al.* (2018) conclude from their results that children over the age of eight form their perception of agent intelligence under the substantial influence of their parents. However, in the current study we focus on student and teacher variables for AI perception.

Research Questions

In the present study we pursue to answer the following research questions (RQ):

RQ1. How does students' motivation and self-efficacy to learn with digital media relate to their perception of AI in learning?

RQ2. Do teacher motivation and self-efficacy to integrate digital media in teaching play a role in this context?

As mentioned in the introduction, research on AI perception is scarce, especially in the primary and secondary school context. It particularly remains uncertain whether research on AI perception in the higher education context can be readily applied to the primary and lower secondary school context, given the systemic differences that exist between these teaching environments. For instance, primary and lower secondary school teachers typically have more interaction and stronger relationships with their students compared to university instructors, and students also vary in terms of their experiences, motivations, and interests (Beder and Darkenwald, 1982). With the present study, we therefore aim to address this research gap and open question by examining our research questions in primary and lower secondary school students (i.e., age 8 to 15) and their respective class teachers.

Furthermore, since several studies indicate the importance of considering class climate effects (e.g., motivation at the class level) from both a theoretical and methodological perspective (Arens *et al.*, 2015; Burić and Kim, 2020; Figlio, 2005; Marsh *et al.*, 2012, 2012; Morin *et al.*, 2014; Ryan, 2000; Volet *et al.*, 2009; Wettstein *et al.*, 2010), our study aims to address this often overlooked aspect.

Methods

The present study was conducted in the context of a large school development program fostering digitalization in elementary school in Switzerland.

Sample

Students and their class teachers from 15 primary and lower secondary schools belonging to 5 school units in German speaking Switzerland were involved in the study. In total 907 students (466 female and 441 male) participated. The mean student age was 11.61 years (*SD* = 1.85 years). The students were clustered into 53 classes taught by 38 female and 15 male class teachers. The mean age of the teachers was 39.32 years (*SD* = 12.42 years) with a mean teaching experience of 14.43 years (*SD* = 12.80 years).

Procedure and Measures

The study was conducted in compliance with ethical standards expressed in the WMA Declaration of Helsinki and all study procedures were deemed appropriate by the author's institution. Students, parents, and teachers were informed about the study's purpose, duration and procedure. Participation was voluntary and written informed consent was given by both students and parents. All data was completely anonymized.
The data collection took place in Spring 2023 through teacher and student online questionnaires containing the measures described in the following along with demographic data (i.e., gender, age, and teaching experience in years). Student questionnaires were completed in class with the class teachers and took the students between 15 and 30 minutes. Teacher questionnaires could be answered individually and took also around 15 and 30 minutes. All teachers and students received an anonymized ID in order to be able to connect student with teacher data.
Most measures used in this study had to be adapted to teaching and learning with digital media from previous studies on teaching and learning in different subjects, as there were no suitable existing measures targeting this topic with younger, primary and lower secondary school students in German. Regarding the student perception of AI as a learning tool, consequently, a completely new scale was constructed. In both questionnaires an image depicting different types of digital media used in the schools was depicted to remind students and teachers of what could all be understand by the term "digital media".
The descriptive statistics as well as the Cronbach's alpha for all measures described below can be found in Table I.

Student motivation to learn with digital media was assessed with a 3-item scale adapted from (Baez *et al.*, 2018). The students were asked about their agreement to the following three statements on an answering scale from 1 = "I do not agree" to 4 = "I agree": (1) I am interested in digital media. (2) I look forward to learning with digital media. (3) I enjoy learning with digital media.

Student self-efficacy to learn with digital media was assessed with a 3-item scale adapted from Baez *et al.* (2018). The students were asked about their agreement to the following three statements on an answering scale from 1 = "I do not agree" to 4 = "I agree": With digital media… (1) ... it is easy for me to participate in class. (2) … I learn quickly. (3) ... it's easy for me to understand something at school.

Student perception of AI in learning was measured with a scale consisting of three items. The items were introduced by the phrase "In a few years it will be possible for a machine with artificial intelligence to help you learn if you get stuck yourself." Then the students were questioned, how much they agreed with the following three statements: (1) "I think the machine could help me a lot." (2) "It would be practical to have such a machine." (3) "I would like to use such a machine." The answering scale ranged from 1 = "I do not agree" to 4 = "I agree".

Teacher motivation to integrate digital media in teaching was measured by a 3-item scale adapted from Vogt *et al.* (2022). Teachers were asked about their agreement from 1 = "I do not agree at all" to 6 = "I completely agree" with the following three statements: (1) "I really enjoy using digital media in class." (2) "I am enthusiastic about stimulating learning processes with digital media for the children in my class." (3) "I find it exciting to watch the children learn with digital media.".

Teacher self-efficacy to integrate digital media in teaching was measured by a 3-item scale adapted from Vogt *et al.* (2022). Teachers were asked about their agreement from 1 = "I do not agree at all" to 6 = "I completely agree" with the following three statements: (1) "I am very familiar with the use of digital media in teaching." (2) "I have many ideas to encourage children to learn using digital media." (3) "I feel competent to support children in learning with digital media.".

Table I.
Descriptive statistics, standardized Cronbach's alpha, and Pearson correlations between the variables.

	Variable name	1	2	3	4	5	6	7	8
1	S AI perception	[0.87]	0.30 ***	0.15 ***	0.03 ***	-0.12 n.s.			
2	S motivation	0.19 n.s.	[0.86]	0.42 n.s.	-0.25 ***	-0.16 n.s.			
3	S self-efficacy	0.17 n.s.	0.58 ***	[0.75]	-0.14 ***	-0.14 ***			
4	S age	0.07 n.s.	-0.66 ***	-0.36 **	-	-0.05 ***			
5	S Gender	0.03 n.s.	-0.19 n.s.	-0.12 n.s.	-0.13 *	-			
6	T motivation	0.08 n.s.	0.14 n.s.	-0.05 n.s.	0.02 n.s.	-0.30 *	[0.84]		
7	T self-efficacy	-0.16 n.s.	-0.04 n.s.	-0.13 n.s.	-0.04 n.s.	-0.16 n.s.	0.71 ***	[0.87]	
8	T experience	0.12 n.s.	-0.02 n.s.	-0.10 n.s.	-0.18 n.s.	0.16 n.s.	-0.07 n.s.	-0.23 n.s.	-
9	T Gender	0.04 n.s.	0.20 n.s.	0.24 t	-0.19 n.s.	0.05 n.s.	0.18 n.s.	-0.08 n.s.	-0.07 n.s.
M		2.85	3.30	3.13	11.61	-	4.66	4.55	14.43
SD		0.83	0.72	0.64	1.85	-	0.88	0.70	12.80

Note. S = Student measures, T = Teacher measures; n.s. $p > 0.1$, t $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$; Cronbach's alphas are depicted in the diagonal in square brackets; Pearson correlations between level 1 variables are shown above the diagonal (*n*=902); Pearson correlations between level 2 variables are shown below the diagonal (*n*=53; to calculate correlations on level 2, student measures were aggregated on the class level).

Data Analysis

Investigating student and teacher variables in the case of the present study implies considering that students are nested in classes instructed by their class teacher. Accordingly, the present data is nested hierarchically, meaning that each school class taught by a class teacher situated on level 2 (L2) contains a set of students situated on level 1 (L1), and that no student is part of multiple school classes. The hierarchical structure of the data was considered by implementing a doubly latent multilevel structural equation approach (Marsh *et al.*, 2009).

Adopting a doubly latent multilevel structural equation approach, allows a decomposition of measurement variance of L1 measures into variance relating to the classroom and variance relating to individual students (Marsh *et al.*, 2009; Ludtke *et al.*, 2011; Preacher *et al.*, 2016). The L2 part of variance can be understood as a class latent aggregation of ratings or class climate effect of a latent variable (Morin *et al.*, 2014; Burić and Kim, 2020; Arens *et al.*, 2015). The residual L1 ratings reflect individual students' distinctive perceptions, which are not accounted for by the shared class perceptions. These unique perceptions may play an important role in understanding and interpreting the results (Morin *et al.*, 2014; Ryan, 2000).

A stepwise analysis approach was applied for the present study. First, the descriptive statistics and Cronbach's alphas were computed regarding all measurement scales. It is commonly assumed that reliable scales should have a Cronbach's alpha exceeding 0.70 (Streiner, 2003; Taber, 2018). Furthermore, Pearson correlation coefficients on L1 and L2 between the variables considered in the present study were computed. While correlations between the variables are expected, correlation coefficients larger than 0.80 would indicate multicollinearity (Berry and Feldman, 1985). Descriptive statistics, Cronbach's alphas as well as Pearson correlations are documented in Table I.

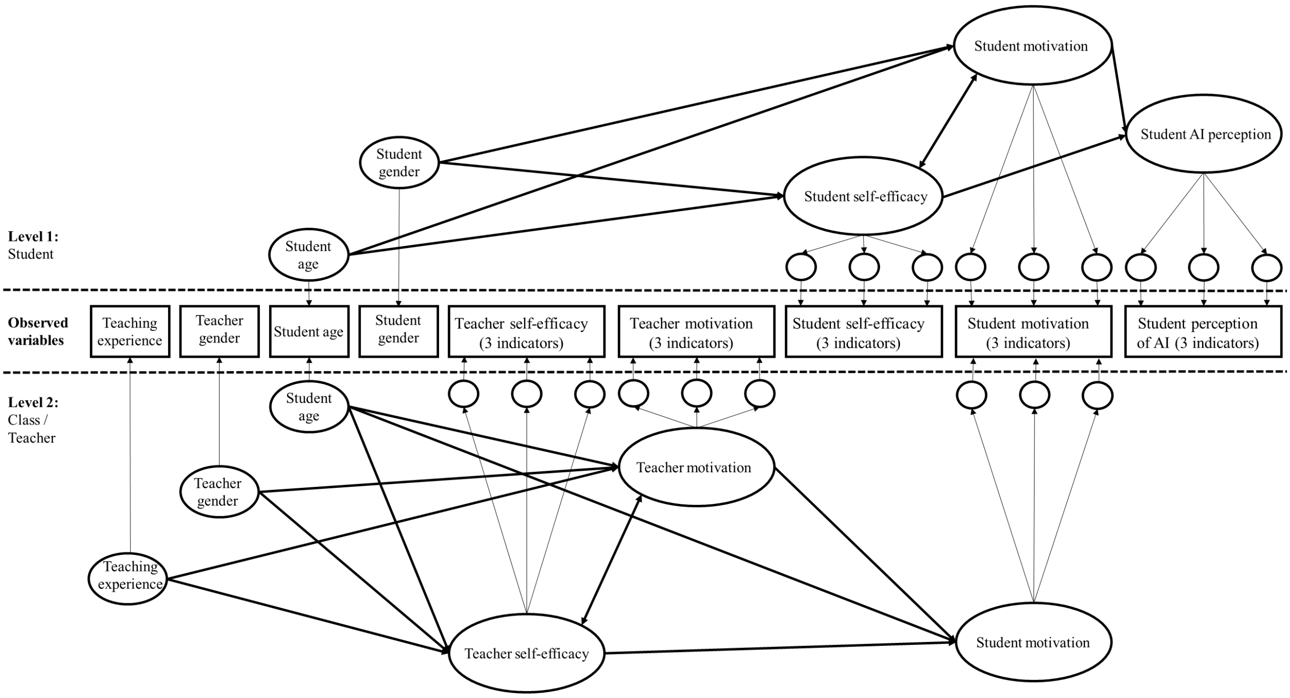
In a next step, a multilevel confirmatory factor analysis was computed (ML-CFA) in order to examine the validity of the two-level latent factor structure. The ML-CFA was inspected regarding model fit parameters (X^2, CFI, TLI, RMSEA, SRMR) as well as the average variance extracted (AVE) and the composite reliability (CR). Regarding the AVE parameter, a value of at least 0.50 is recommended, while regarding the CR a value of at 0.70 or larger is recommended (Fornell and Larcker, 1981; Hair *et al.*, 2006; Huang *et al.*, 2013). Based on the model, the intraclass correlation coefficients (ICC values) are reported. ICC values reflect the similarity of ratings between units at L1 (Koo and Li, 2016), i.e., the students in a school class.

Finally, a multilevel structural equation model (ML-SEM) was computed and tested (X^2, CFI, TLI, RMSEA, SRMR). The model is depicted in Figure 1 and it was structured following the model by Burić and Kim (2020). To assess the model fit parameters, the following cut off scores were considered: CFI and TLI ≥ .95, RMSEA ≤. 06, SRMR ≤ .08 (Burić and Kim, 2020; Hu and Bentler, 1999; Morin *et al.*, 2014).

For the ML-CFA and ML-SEM analyses, a maximum likelihood parameter estimate with robust standard

errors (MLR) was chosen in order to address the student measures violation of multivariate normality (Little and Rubin, 2002).
Data management and analyses were conducted using the R software environment (R Core Team, 2023). For the multilevel structural equation models the lavaan R package was used (Yves Rosseel, 2012).

Figure 1.
Examined multilevel structural equation model on the interplay of student and teacher motivation on student perception of AI.



Results

In the following the results of the above-described stepwise analysis approach are reported.

Multilevel Confirmatory Factor Analysis (ML-CFA)

The standardized factor loading estimates as well as the model fit statistics for the ML-CFA are described in Table II. The model fit statistics indicate a good fit of the model.
Student perception of AI and student self-efficacy were not considered on L2 as Ludtke *et al.* (2011) as well as Marsh *et al.* (2012) propose that ICC values should be around 0.1 or larger in order to consider a variable for variance decomposition on the two levels of analysis.

Table II.
Standardized factor loading estimates and model fit statistics of the robust multilevel confirmatory factor analysis (n = 907 students, n = 53 teachers; all $p < 0.001$).

			L1			L2		ICC values
L1: Student	Items	1	2	3	2	6	7	
1 Perception of AI	a	0.78			0.90			0.00
	b	0.86			0.98			0.00
	c	0.84			1.00			0.00
2 Student motivation	a		0.67					0.05
	b		0.91					0.10
	c		0.84					0.10
3 Student self-efficacy	a			0.63				0.00
	b			0.75				0.00
	c			0.74				0.00
L2: Class & Teacher								
6 Teacher motivation	a					0.88		
	b					0.82		
	c					0.70		
7 Teacher self-efficacy	a						0.80	
	b						0.82	
	c						0.88	
Model fit								
X^2		2938.05						
df		72.00						
CFI		1.00						
TLI		1.01						
RMSEA		0.00						
SRMR		L1 = 0.04			L2 = 0.05			
AVE		0.69	0.66	0.50	0.92	0.64	0.69	
CR		0.87	0.85	0.75	0.97	0.84	0.87	

Note. df = degrees of freedom; *CFI* = Comparative Fit Index; *TLI* = Tucker-Lewis Index; *RMSEA* = Root Mean Square Error of Approximation; *SRMR* = Standardized Root Mean Square Residual; *AVE* = Average Variance Extracted; *CR* = Composite Reliability.

Multilevel Structural Equation Model (ML-SEM)

The standardized estimates and model fit statistics of the robust multilevel structural equation model are reported in Table III. Model fit parameters indicated a satisfactory fit.

Regarding research question 1 (RQ1: The role of the student) results show that student motivation was significantly positively correlated with student self-efficacy to learn with digital media ($\beta = 0.43, p < 0.001$). Student motivation to learn with digital media was significantly associated with a more positive perception of AI in learning ($\beta = 0.29, p < 0.001$). Female students exhibited lower self-efficacy to learn with digital media ($\beta = -0.17, p < 0.001$). Student age (i.e., at the class level) was negatively related to student motivation to learn with digital media (i.e., at the class level; $\beta = -0.91, p < 0.001$).

Regarding research question 2 (RQ2: The role of the teacher) results show that teacher motivation to integrate digital media in teaching was significantly positively correlated with teacher self-efficacy to integrate digital media in teaching ($\beta = 0.86, p < 0.001$). Teacher motivation to integrate digital media in teaching was also significantly positively associated with student motivation to learn with digital media at the class level ($\beta = 0.71, p < 0.01$). When controlling for the correlation with teacher motivation, teacher self-efficacy to integrate digital media in teaching was significantly negatively associated with student motivation to learn with digital media at the class level (β = -0.63, p < 0.05).

Table III.
Standardized estimates and model fit statistics of the robust multilevel structural equation analysis (n = 907 students, n = 53 teachers; two-sided p-values).

			Estimate	***p***	***R^2***
L1 effects					0.47
Perception of AI	regressed on	Student motivation	0.29	< 0.001	
	regressed on	Student self-efficacy	0.06	0.262	
Student motivation	regressed on	Student age	-0.15	0.222	
	regressed on	Student gender	-0.05	0.153	
	correlated with	Student self-efficacy	0.43	< 0.001	
Student self-efficacy	regressed on	Student age	-0.10	0.542	
	regressed on	Student gender	-0.17	0.001	
L2 effects					0.64
Student motivation L2	regressed on	Student age L2	-0.91	< 0.001	
	regressed on	Teacher motivation	0.71	0.004	
	regressed on	Teacher self-efficacy	-0.63	0.032	
Teacher motivation	regressed on	Student age L2	0.07	0.663	
	regressed on	Teaching experience	-0.14	0.371	
	regressed on	Teacher gender	0.24	0.216	
	correlated with	Teacher self-efficacy	0.86	< 0.001	
Teacher self-efficacy	regressed on	Student age L2	-0.11	0.552	
	regressed on	Teaching experience	-0.25	0.183	
	regressed on	Teacher gender	-0.12	0.487	
Model fit					
X^2	2280.66				
df	119.00				
CFI	1.00				
TLI	1.04				
RMSEA	0.00				
SRMR	L1 = 0.08				
	L2 = 0.08				

Note. df = degrees of freedom; *CFI* = Comparative Fit Index; *TLI* = Tucker-Lewis Index; *RMSEA* = Root Mean Square Error of Approximation; *SRMR* = Standardized Root Mean Square Residual; *AVE* = Average Variance Extracted; *CR* = Composite Reliability.

Discussion

The present study aimed to address two research questions: the role of student motivation and self-efficacy to learn with digital media in relation to their perception of AI in learning (RQ1) and the role of teacher variables (RQ2) in shaping primary and lower secondary school students' perception of AI in learning. Several important insights as well as implications for practice have emerged.

Discussion of Results and Implications

With respect to the first research question (RQ1) student motivation to learn with digital media at the individual level was found to play a pivotal role in shaping their perception of AI in learning. Additionally, student self-efficacy to learn with digital media is important for driving student motivation to learn with digital media, which has been supported by previous research, emphasizing the importance of fostering self-efficacy, especially with regard learning environments that are technologically integrated such as AI (Bandura, 2003; Chai *et al.*, 2021). The observed gender differences in self-efficacy to learn with digital media are consistent with previous findings on ICT self-efficacy girls (Cai *et al.*, 2017; Whitley, 1997; Yu and Hu, 2022) and indicate that this seems to be particularly important in female students. Consequently, instructional approaches are needed that further consider individual differences in learners when addressing AI perception. Researchers can investigate the effectiveness of such approaches by applying learner-treatment-interaction study designs.

Notably, individual student age did not show significant effects, but student age at the class level plays a significant role for motivation to learn with digital media in such a way, that the older the class (higher grade) the lower the motivation, as seen in prior studies on academic motivation (Gottfried *et al.*, 2001; Lepper *et al.*, 2005). Concerning implications for practice, these results emphasize the need for promoting a positive perception of AI, especially in the early stages of education, and the importance of tailored approaches for students in different grades. To support teachers in developing these tailored approaches, professional development regarding AI literacy is needed. For such professional development programs, research-based approaches like suggested in the Tell-Show-Enact-Do learning design (Buchner and Hofmann, 2022) based on the Synthesis of Qualitative Data model (Tondeur *et al.*, 2012) might be helpful as a blueprint.

Turning to the second research question (RQ2) concerning the role of the teacher, teacher motivation to integrate digital media into teaching plays an important role for student motivation to learn with digital media at the class level. This can be interpreted in such a way that teacher motivation to integrate digital media in teaching can positively impact the class climate. As a result, we expect an indirect effect on students' perception of AI in learning. That is, higher teacher motivation to integrate digital media in teaching contributes to higher students' motivation to learn with digital media at the class level, which in turn, as found in the current study, contributes to a more positive perception of AI in learning at the individual student's level. However, more research is necessary to further verify this assumption.

Similar as in students and in line with previous research, teacher motivation to integrate digital media into teaching was also interrelated with teacher self-efficacy to integrate digital media into teaching. Accordingly, teachers who feel confident to integrate digital media into their teaching (i.e., high self-efficacy) are more motivated and enthusiastic about stimulating learning processes with digital media. Since, as stated above, teacher motivation to integrate digital media in teaching can be expected to be important for shaping students' perception of AI in learning, this highlights the importance of fostering teacher self-efficacy regarding the use of digital media. As shown in digital teacher education and professional development literature, fostering technological, pedagogical, and content knowledge (TPACK; Mishra and Koehler, 2006) contributes to the development of digital media self-efficacy in teachers (Zeng *et al.*, 2022). Therefore, in teacher education and training instructional approaches should be used that promote TPACK like the learning technology by design approach (Buchner and Zumbach, 2020; Koehler and Mishra, 2005) or specific TPACK-modules, which are based on Tondeur *et al.* (2012)'s SQD model (e.g. Lachner *et al.*, 2021). The importance of TPACK for education in the age of AI is also outlined most currently by Mishra *et al.* (2023).

However, when controlling for its relation with teacher motivation, teacher self-efficacy exhibits negative associations with student motivation to learn with digital media at the class level. This could be interpreted in such a way that teachers' excessive self-efficacy to integrate digital media in teaching might be perceived as negative by the class and might deter the class engagement in exploration and increase their fear of failure when using new technologies for learning such as AI. This highlights the complex interplay between teacher beliefs and the classroom environment and is worth investigating in future studies.

Strengths, Limitations, and Future Research

It is important acknowledge that teacher-student motivation is a reciprocal relationship, with students potentially influencing (i.e., "motivating") teachers as well. However, the current cross-sectional model does not allow for testing these reciprocal effects, indicating the need for longitudinal studies to gain a more comprehensive understanding of these dynamics. With such longitudinal studies one could also examine changes in students' perception of AI for example, depending on the level of incorporation of AI concepts within school curricula. However, given the scarce research on students' AI perception in learning in lower educational levels, our study can be seen as a first step in closing this research gap by investigating students and teachers from primary and lower secondary schools.

Moreover, the way we built our analyses allowed for the examination of student and teacher variables within a single multilevel model, accommodating the hierarchical data structure (students nested within classes instructed by their class teacher). This is a clear extension compared to prior research.

Furthermore, the doubly latent multilevel structural equation modeling (ML-SEM) approach also took into account the "class climate" (i.e., student motivation at the class level). Since motivation arises from the interplay between individuals within the social environment of the classroom and school (Urdan and Schoenfelder, 2006), this factor (i.e., class climate) is next to the individual student and the teacher also worth considering, but researchers have rarely done it so far. While this study takes a significant step in addressing this gap, researchers should explore this interplay more extensively in future studies.

In this respect, descriptive results of the current study indicate that the composition of the class might play a role for teacher motivation in such a way that in classes with a high percentage of boys, teachers are more motivated to incorporate digital media in their teaching. In contrast, the students themselves do not exhibit differences in motivation to learn with digital media, but they do differ in self-efficacy when it comes to learning with digital media. It would be certainly interesting to delve deeper into this aspect and consider how to address gender-related differences in this context.

An additional extension of the current study and thus a revenue for future research would involve considering additional variables, such as parents or family. As previously mentioned in the introduction (Druga *et al.*, 2018), these variables could potentially exert a substantial influence on students' perceptions of AI in learning.

Conclusion

In conclusion, for a more positive perception of AI in learning in primary and lower secondary school students, the present study highlights the importance of fostering students' self-efficacy and motivation to learn with digital media, particularly among female students using tailored instructional approaches that consider individual differences. Additionally, it emphasizes the need for a supportive and motivating teacher-student dynamic to create a more positive perception of AI in learning. In this context, providing professional development in AI literacy for teachers can be an essential step. These insights are valuable in guiding the integration of AI in primary and lower secondary school settings. Furthermore, the findings underscore the need for further research to advance our knowledge in this area (e.g., longitudinal studies and studies that investigate parental and family influences on students' perception of AI in learning).

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