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Exploring AI perceptions in education: unveiling the role of student and teacher motivation and self-efficacy

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A R T I C L E I N F O

Keywords:
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A B S T R A C T

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 is positively associated with their motivation, with girls exhibiting lower self-efficacy to learn with digital media compared to boys. At the class level, teachers' 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 into primary and lower secondary school settings.

1. 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 [1,2], which in turn underscores the necessity for further studies in the field of AI and education. On the one hand, this is crucial to provide research-based information for educational practice regarding the future of education in an AI-shaped world. On the other hand, it is vital for addressing and answering the research gaps and open research questions identified in recent systematic literature reviews on AI in education. For example, examining systematic reviews [3–5] reveals that research on AI in education focusing on the lower levels is still in its infancy. For instance, a recent systematic review of 155 empirical AI-in-education studies published between 2015 and 2025 shows that most studies are in higher education and identifies primary and secondary education as under-researched contexts [5]. Especially at a young age, children should be taught the basic AI concepts in order to develop AI literacy [7–9]. Current literature points to a growing need for more research on students` perceptions of AI toward fostering AI literacy among children [10–12]. Ottenbreit-Leftwich et al. [13] 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. While AI-specific research remains limited, previous research indicates that students' intrinsic motivation to learn with digital media and their digital self-efficacy can play an important role in shaping engagement and learning behaviors in school contexts. For example, Dong [14] found that in upper-secondary students, higher self-efficacy was associated with stronger intrinsic motivation to learn with digital media, which in turn predicted greater engagement in technology-enhanced learning tasks. These findings raise the question of

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whether motivational and self-efficacy beliefs that support learning with digital media may also be relevant when students encounter AI-based learning tools, which can be regarded as a specific type of digital learning technology. This potential link has not yet been empirically examined.

In the context of the present study, we refer to AI in a broad sense as any artificial intelligence application capable of supporting students' learning processes in everyday school life. One example would be providing help when learners encounter difficulties. This conceptualization does not limit AI to a specific technology (e.g., generative AI, rule-based systems, or machine learning) but rather addresses students' general perceptions of AI as a potential learning assistant. 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. [15], 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.

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

1.1. Student variables affecting students' perceptions of AI in learning

1.1.1. Student motivation

To begin, we will 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 [16–18]. In the school context research suggests that it arises from the interplay between individuals within the social environment of the classroom and school [19] and it is considered a fundamental education variable as it is a critical component of learning [20–22].

In motivational psychology, motivation is commonly categorized into 'intrinsic motivation' and 'extrinsic motivation,' as outlined in self-determination theory by Ryan and Deci [23]. 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 [23–24], 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 [25], with self-efficacy being a major aspect.

In the present study, intrinsic motivation to learn with digital media refers to students' self-determined enjoyment, interest, and curiosity in learning activities involving digital media. Previous research in school contexts indicates that higher intrinsic motivation in technology-enhanced learning is linked to greater engagement [14]. AI-based learning tools can be considered a specific type of digital media in that they require similar interactions, technological skills, and openness to new ways of learning. Motivational mechanisms that foster engagement with digital media may therefore also play a role when students in primary and lower secondary school encounter AI in learning. Recent empirical studies [26] have begun to examine this potential transfer in primary and lower secondary school settings, demonstrating that motivational mechanisms relevant for digital media engagement can also play a role when students encounter AI-based learning tools.

1.1.2. Student self-efficacy

Self-efficacy is a comprehensive concept which goes back to Bandura [27] 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 [28]) and it is important for motivation [29, 30]. 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 [27].

Digital media self-efficacy draws upon [27]'s concept and can be described as the degree to which a person believes they can proficiently operate digital media [31]. 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 [28]).

In relation to students' perceptions and use of digital media, research by Aesaert and van Braak [32] 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 [33] 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 [34]. Chen [35] found that students' computer self-efficacy contributes to their learning engagement and, in turn, their learning performance. Also, Tseng [36] 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 [37]. Chai et al. [38] 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 everyday 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.

Given that AI-based learning tools can be considered a specific type of digital media, students' confidence in their ability to effectively use digital technologies is likely to be relevant for how they perceive and approach AI in learning. Digital media self-efficacy may support the exploration of AI tools, reduce perceived barriers to their use, and foster openness to integrating them into learning processes. However, while there is growing evidence that digital media self-efficacy relates to students' engagement in technology-enhanced learning [e.g., 32,35], empirical research directly examining its relationship with students' perceptions of AI in learning, particularly in primary and lower secondary school contexts, remains scarce. Addressing this gap is one of the aims of the present study.

1.1.3. Student age

Since demographic differences in the development of students' motivational profiles and a corresponding need for different supports are noted in several studies [39], 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 [40–42].

The observed decline in intrinsic motivation across school years has been explained by developmental and contextual factors such as reduced autonomy support, increased performance pressure, changes in peer norms, and shifts in perceived competence [40–42]. Given the central role of motivation in shaping students' learning engagement (see Section 1.1.1. on student motivation), examining age-related differences provides important context for understanding potential variation in students' perceptions of AI in learning.

1.1.4. Student gender

Similarly, gender has been shown to influence the relationship between students' motivation and the topic or context of the learning task [43]. When looking at digital media, meta-analytic findings indicate that boys reported higher level of ICT self-efficacy and interest compared to girls [44–46]. Regarding the perception of computers Meelissen and Drent [33] 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).

Gender differences in attitudes toward digital media have been linked to factors such as differential socialization, stereotypical beliefs about technology, and varying access to and experience with digital tools [44,45]. As outlined in the sections on student motivation and self-efficacy, such factors can affect both interest in and confidence with technology. Including gender as a variable in the present study therefore allows us to explore whether these patterns also extend to students' perceptions of AI in learning.

1.2. Teacher variables affecting students' perceptions of AI in learning

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. In primary school, students are usually taught by a main class teacher, supported by a small team of subject teachers, each responsible for one or multiple subjects [47,48], while in lower secondary school, instruction becomes more subject-specific [49]. Nevertheless, class teachers at both levels remain key figures in students' school lives. In the Swiss context, class teachers in lower secondary education not only coordinate administrative matters, but are also responsible for the overall well-being of students, lead activities such as class camps, and serve as the primary contact person for students and parents [50]. Research shows that teachers, through their interpersonal styles and motivational support, can have a lasting influence on students' school-related engagement and motivational beliefs [51,52].

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 [53–56].

1.2.1. Teacher motivation

Studies have established a connection between teacher motivation and student motivation [57–60], which, in turn, as stated 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 rationale 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 [61–63]. 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 [64].

Empirical evidence supports our idea that teacher motivation can exert a positive influence on student motivation for learning [57–60] 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 [65,66].

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 [67]. 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 [68,69]. 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.

1.2.2. Teacher self-efficacy

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 [42,70,71, meta analysis by 72,73]. Ertmer [74] and Ertmer and Ottenbreit-Leftwich [75] 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 [76]. For instance, Daumiller et al. [77] 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. [78] found associations between teacher self-efficacy and student motivation to learn in primary school.

Teachers' technological knowledge, prior experience with digital tools, and orientations toward emerging technologies, including AI-based learning tools, may shape their self-efficacy in technology integration. These factors, including perceptions of controllability, perceived pedagogical value, and epistemic beliefs about the role of AI in knowledge construction, can shape how teachers frame technology use in the classroom and how confidently they introduce new digital tools to students [75]. Such teacher behaviors and signals may serve as important cues for students' own appraisals of AI, particularly when they have limited prior experience. Beyond providing instructional guidance, teachers also convey implicit messages about trust, uncertainty, and the legitimacy of AI supported learning [38]. Although the present study did not assess AI-specific teacher readiness or knowledge directly, recent literature suggests these factors are potentially influential in shaping teacher self-efficacy and, indirectly, students' perception of AI-supported learning [79,80].

1.2.3. Summary on teachers' role on students' perceptions of AI in learning

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.

1.3. Further variables affecting students' perceptions of AI in learning

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 [81], 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 [82]. Meelissen and Drent [33] 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. [83] 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.

1.4. Interplay of teacher and student variables affecting students' perceptions of AI in learning

As previously stated, existing 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 [84]. 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 [85–92], our study aims to address this often overlooked aspect.

While class climate represents one important contextual layer in the school environment, it should be noted that additional school-related factors such as peer interaction patterns, teacher collaboration, or infrastructural and technical-pedagogical support may also influence students' perceptions of AI in learning. However, these aspects were not the primary focus of the present study, which centers on student- and teacher-related motivational factors. Investigating such broader contextual variables would go beyond the scope of this first investigation.

1.5. Research questions

Consequently, 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, as well as class-level student age, predict aggregated student motivation to learn with digital media?

2. Methods

The present study was conducted in the context of a large school development program fostering digitalization in elementary school in Switzerland. The quantitative data set, excluding participant characteristics, is available from the corresponding author upon a reasonable request.

2.1. Sample

Students and their class teachers from 12 primary and 3 lower secondary schools belonging to 5 school units in German speaking Switzerland were involved in the study. In total 907 students (466 female, 441 male; 639 primary, 268 lower secondary school students) participated. The mean student age was 11.61 years (*SD* = 1.85 years). The students were clustered into 53 classes (36 primary, 17 lower secondary) 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).

In the Swiss education system, primary school (grades 1–6; ages approximately 6–12) is typically taught by a main class teacher, supported by a small team of subject teachers, each responsible for one or multiple subjects [47,48]. In lower secondary school (grades 7–9; ages approximately 12–15), teaching is more subject-specialized, with students usually taught by many different teachers, each covering one or a few subjects [49].

All participating schools were involved in a multi-year school development program focused on the pedagogical integration of digital media, and both primary and lower secondary classes had regular access to classroom computers or tablets.

2.2. 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 St.Gallen University of Teacher Education. According to the policy at the St.Gallen University of Teacher Education, no specific ethical approvement was necessary for conducting this study. 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 min. Teacher questionnaires could be answered individually and took also around 15 and 30 min. All teachers and students received an anonymized ID to be able to connect students 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 1. Construct validity of the student measures (motivation to learn with digital media, self-efficacy to learn with digital media, and perception of AI in learning) was examined using a multilevel confirmatory factor analysis (ML-CFA; see Section 2.3 and 3 for the procedure and results).

Student (intrinsic) motivation to learn with digital media was assessed with a 3-item scale [adapted from 93]. 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. Cronbach's alpha for the adapted version was 0.86 (see Table 1).

Student self-efficacy to learn with digital media was assessed with a 3-item scale [adapted from 93]. 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. Cronbach's alpha for this adapted version was 0.75 (see Table 1).

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

Table 1
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
Skewness		−0.44	−1.04	−0.68	0.41	-	−0.96	−0.18	0.75
Kurtosis		−0.51	0.63	0.42	−0.08	-	1.27	−0.53	−0.75

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).

scale ranged from 1 = "I do not agree" to 4 = "I agree". Cronbach's alpha for this scale was 0.87 (see Table 1).

Teacher motivation to integrate digital media in teaching was measured by a 3-item scale adapted from Vogt et al. [94]. 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.". Cronbach's alpha for this adapted scale was 0.84 (see Table 1).

Teacher self-efficacy to integrate digital media in teaching was measured by a 3-item scale adapted from Vogt et al. [94]. 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.". Cronbach's alpha for this adapted scale was 0.87 (see Table 1).

2.3. Data analysis

Investigating student and teacher variables in the case of the present study implies 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 [95].

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 [95–97]. The L2 part of variance can be understood as a class latent aggregation of ratings or class climate effect of a latent variable [85,86,89]. 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 [89,90].

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 [98,99]. 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 [100]. Descriptive statistics, Cronbach's alphas as well as Pearson correlations are documented in Table 1.

Next, 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 [101–103] Based on the model, the intraclass correlation coefficients (ICC values) are reported. ICC values reflect the similarity of ratings between units at L1 [104], 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 Fig. 1 and it was structured following the model by Burić and Kim [86]. To assess the model fit parameters, the following cut off scores were considered: CFI and TLI ≥ 0.95, RMSEA ≤. 06, SRMR ≤ 0.08 [86,89,105].

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 [106]

Data management and analyses were conducted using the R software environment [107]. For the multilevel structural equation models the lavaan R package was used [108].

In the model depicted in Fig. 1, Level 1 represents relationships between individual student variables within classes: intrinsic motivation to learn with digital media, self-efficacy to learn with digital media, and perception of AI in learning. At this level, intrinsic motivation and self-efficacy are modeled as correlating with each other, and both are specified as predictors of AI perception. Level 2 represents relationships between aggregated class-level student motivation and teacher variables (motivation and self-efficacy to integrate digital media in class), as well as class-average student age. At this level, student motivation is treated as a latent class factor predicted by teacher motivation, teacher self-efficacy, and class-level student age. In this modelling approach, the variance of student motivation is decomposed into two parts: variation within classes (level 1: differences between students in the same class) and variation between classes (level 2: differences between classes as a

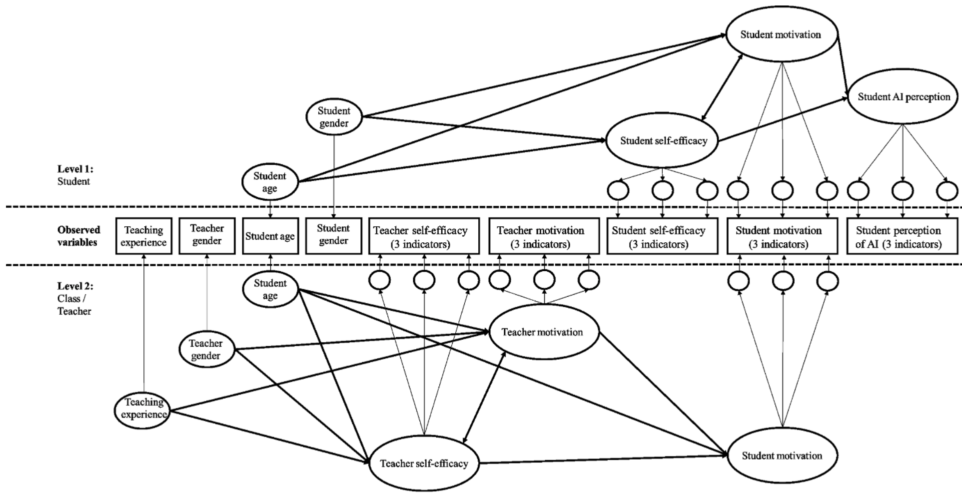

Fig. 1. Examined multilevel structural equation model on the interplay of student and teacher motivation on student perception of AI.

whole).

AI perception was only modelled at Level 1 because it did not exhibit meaningful between-class variance in our data (see Section 3.1 for ICC values). In contrast, intrinsic motivation to learn with digital media showed sufficient between-class variance to be modelled at Level 2, where it served as variable predicted by teacher motivation, teacher self-efficacy, and class-level student age.

In the modelling approach used, there is one dependent variable at each level: at level 1, students' perception of AI in learning; at level 2, aggregated class-level student motivation to learn with digital media. These two outcomes are conceptually linked: teacher motivation and self-efficacy at level 2 are associated with class-level student motivation, which in turn is related to individual student motivation at level 1, ultimately predicting the perception of AI in learning. This structure allows the model to capture both the within-class processes (individual motivation and self-efficacy shaping AI perception) and the between-class processes (teacher and class climate effects shaping class-level motivation) within the same framework.

3. Results

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

3.1. 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 2. 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. [96] as well as Marsh et al. [88] 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 2
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.

3.2. Multilevel structural equation model (ML-SEM)

The standardized estimates and model fit statistics of the robust multilevel structural equation model are reported in Table 3. 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) the 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 ($\beta = -0.63$, $p < 0.05$).

Table 3
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					
χ^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.

4. 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.

4.1. 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 associated with students' perception of AI in learning. Additionally, student self-efficacy to learn with digital media is positively associated with student motivation to learn with digital media, which has been supported by previous research, emphasizing the importance of fostering self-efficacy, especially regarding learning environments that are technologically integrated such as AI [29,38]. The observed gender differences in self-efficacy to learn with digital media are consistent with previous findings on ICT self-efficacy [44–46] 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 [40,41]. 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 [109] based on the Synthesis of Qualitative Data model [110] might be helpful as a blueprint.

Turning to the second research question (RQ2) concerning the role of the teacher, teacher motivation to integrate [29,38] digital media into teaching is linked with higher student motivation to learn with digital media at the class level. This can be interpreted in such a way that teacher motivation to integrate [44–46] digital media in teaching is positively associated with class climate, which might indicate an indirect effect of teacher motivation on students' perception of AI in learning. That is, higher teacher motivation to integrate digital media in teaching might contribute to higher students' motivation to learn with digital media at the class level, which in turn, might contribute 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 to 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 with higher self-efficacy in integrating digital media into their teaching report higher motivation to stimulate 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 technology-related teaching skills [111] contributes to the development of digital media self-efficacy in teachers [6]. Therefore, one important implication of this study is that in teacher education and training instructional approaches should be used that promote technology-related teaching skills like the learning technology by design approach [112,113] or other research based instructional approaches to foster AI technology-related teaching skills [e.g., 114, 115].

Unexpectedly, after controlling for teacher motivation, teacher self-efficacy showed a negative association with student motivation to learn with digital media at the class level. This counterintuitive finding suggests that the relationship between teacher beliefs and student motivation may be more complex than previously assumed. One possible explanation is that highly self-efficacious teachers may implement more challenging instructional strategies, which may not immediately align with all students' motivational preferences. In some cases, teachers' excessive confidence in integrating digital media could be perceived as negative by the class, possibly discouraging exploration and increasing students' fear of failure when using new technologies for learning such as AI. Controlling for teacher motivation may also isolate aspects of self-efficacy that relate differently to student engagement. Contextual factors such as grade level of subject matter may further moderate this relationship. Overall, this highlights the complex interplay between teacher beliefs and the classroom environment and underscores the need for further research to disentangle the conditions under which teacher self-efficacy positively or negatively affects student motivation and is worth investigating in future studies.

4.2. *Strengths, limitations, and future research*

It is important to 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, relating to the level of incorporation of AI concepts within school curricula. However, given the scarce research on students' AI perception in learning at 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 considered 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 [19], 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. This aspect could, for example, be addressed by supplementing the presented quantitative study with qualitative or mixed methods research, thereby facilitating a more profound investigation into perceptions and collective interpretations of AI in learning by students and/or teachers.

Another direction of future research could be based on descriptive results of the current study indicating 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 tend to report higher motivation 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.

Moreover, it would be beneficial to investigate the use of and access to AI by students in further research. While this study focused on general perceptions and motivational aspects, we did not include more fine-grained indicators of teachers' technological knowledge, such as training or experience with specific digital or AI tools. Likewise, we did not systematically assess the technological infrastructure of participating schools, although all schools were involved in a digital development program and had regular access to computers or tablets. Future studies should address these contextual and competence-related factors more explicitly to better understand associations between technological readiness and student and teacher perceptions. For example, it would be valuable to ascertain how teachers promote the use of AI in the classroom, what AI tools and resources are available to students for academic purposes and how often they are used in different grades. Also, it would be interesting to research whether students use AI tools outside of the classroom for purposes unrelated to their studies.

While this study already accounted for class-level motivational climate through multilevel modelling, future research could further extend the analysis of school context by including additional factors such as peer interaction patterns, school leadership, or infrastructural support, as these may affect students' engagement with AI-related technologies and learning environments more directly.

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 [83], these variables could potentially be associated with students' perceptions of AI in learning.

5. 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 that a supportive and motivating teacher-student dynamic may support 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).

CRediT authorship contribution statement

Charlotte Baez: Writing – review & editing, Writing – original draft, Project administration, Methodology, Formal analysis, Data curation, Conceptualization. **Josef Buchner:** Writing – review & editing, Writing – original draft, Methodology. **Anna-Lena Ullrich:** Writing – review & editing, Writing – original draft. **Stefanie Schallert-Vallaster:** Writing – review & editing, Writing – original draft.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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