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Science educators' AI literacy and AI usage in teaching: Implications for post-qualification programs

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ABSTRACT

Artificial Intelligence (AI) is becoming increasingly relevant in both professional and everyday contexts, making its integration into educational curricula essential. In addition, teachers can use AI to support lesson planning, implementation, and follow-up. To leverage these opportunities effectively, teachers require AI-related knowledge and competencies that enable them to optimize its use and prepare students for an AI-driven world. This study investigates the need for AI-related post-qualification programs for in-service science educators and identifies relevant areas of focus. Therefore, the study investigated the extent to which in-service science educators in secondary education possess general AI knowledge (AI literacy) and how, why, and for what purposes they use AI in lesson planning and follow-up, as well as in teaching. To answer these questions, $n = 115$ in-service science educators from Germany and Switzerland were surveyed. Quantitative data on AI usage and AI literacy were collected via questionnaires; in addition, $n = 21$ of the surveyed teachers were interviewed to provide qualitative support for our findings. The results of the study indicate a clear need for AI-related post-qualification programs. Although in-service science educators possess generally solid level of AI literacy, no significant correlation was found between their level of AI literacy and the actual use of AI in educational practice. Analysis of reported usage areas suggests that post-qualification programs should place a stronger emphasis on school- and subject-specific AI literacy and on concrete subject-specific applications of AI in science education.

1. Introduction

1.1. The impact of AI on science education

Artificial Intelligence (AI) has gained considerable importance in recent years. Particularly, the advancements in generative AI have had a significant impact, as they introduced novel possibilities and challenges, profoundly influencing various areas of everyday life such as healthcare [1,2], finance [3], and communication [4]. In addition to its integration into our everyday lives, we are already seeing the adoption of artificial intelligence into scientific research and applications [5–8]. This integration spans various research areas and reveals the enormous potential, as well as the associated risks and challenges of using AI.

Overall, AI's technical development and integration are resulting in social and professional changes. In this context, the EU has responded with an update of DigComp 2.2 - a Europe-wide framework that describes key competencies to be developed in relation to digital technologies - which now also includes AI [9]. The promotion of AI-related skills has been cited internationally in various frameworks and guidelines to empower citizens to participate in an increasingly data-driven society [10,11]. AI skills can be described as elements of 21st-century key competencies in this context. To prepare for the changes in society and the professional landscape mentioned earlier, AI must play a more significant role in education, especially given the already frequent and often unguided use of generative AI tools by students [12,13]. Thus, the need to empower students to use AI responsibly and question AI critically arises. In addition, students should be introduced to the use of AI across various professions to illustrate the relevance of this

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technology for their future careers (e.g., Shamir and Levin [14]). AI should therefore be addressed not only in terms of its technical and societal contexts, but also specifically within a subject-specific context. At the same time, AI in the educational context is being researched with respect to its potential impact on students, for example, its positive effects on creative problem-solving skills [15] or on improved academic performance [16].

Given that AI affects learning, it is also a useful tool for teaching. AI helps teachers to plan, implement, and follow up lessons more efficiently and adaptively [17]. This includes, for example, uses such as the creation and evaluation of tests [18,19], planning field trips [20], generating learning materials [21], as well as providing personalized feedback [22, 23]. Finally, teachers have the opportunity to integrate teaching about AI into their lessons; this includes, for example, instruction on AI within the subject [24], how AI works [25], and the need to take a critical look at this technology [26].

1.2. AI competencies of science educators

In order to use AI effectively as a teaching tool or as a subject matter, teachers must have appropriate AI-related competencies. Only by acquiring the necessary AI competencies teachers can a) use this technology to, e.g. generate helpful learning materials for students and plan adaptive instruction, as well as b) educate students about the (subject-specific) potentials and risks of using AI and teach them how to use it. AI-related competencies must be systematically and structurally integrated into teacher education, training programs and professional development to achieve this. However, the question remains open: Which competencies of in-service teachers must be improved based on an existing (yet unknown) knowledge base?

Established frameworks and models have provided a foundation for pre-service teacher education for the past years by describing technology-unspecific Information and Communication Technology (ICT) competencies required by teachers in secondary education. An example of such a basic framework encompassing technology-unspecific ICT competencies is the TPACK model [27]. TPACK is based on three areas: technological knowledge (TK), pedagogical knowledge (PK), and content-related knowledge (CK). Their overlaps give rise to further areas of knowledge: technological-pedagogical knowledge (TPK), pedagogical-content knowledge (PCK), and technological-content knowledge (TCK). The intersection of all areas leads to technological pedagogical content knowledge (TPACK; Koehler et al. [27]). Similar subject- and technology-unspecific frameworks exist at the European level, describing the digital competencies required for teachers (e.g., the European digCompEdu [28], the Austrian digi.kompP [29] or the Spanish CDCFT [30]). As AI is a digital technology, the question arises whether these frameworks already include AI. Even if we assume that these frameworks already implicitly include general AI competencies, it is still unclear what (subject-)specific AI competencies teachers actually possess. Consequently, it must be noted that in-service teachers may need appropriate AI related post-qualification training in the areas of TK, TCK, TPK, and TPACK. In this context, the technology-associated component of the TPACK model (introduced by TK) refers to AI, which is why the following terms TK^{AI}, TCK^{AI}, TPK^{AI}, and $TPACK^{AI}$ (in accordance with Celik [31] and Ning et al. [32]; see Fig. 1) are used. However, due to the lack of subject-specific focus in these models, they cannot be used to develop subject-specific competency tests, nor do they provide a basis for deriving meaningful content for such continuing education programs from the resulting competency profiles. Guidance on what content such post-qualification programs should cover can be derived, on the one hand, from an assessment of teachers' existing general AI literacy and, on the other hand, from an assessment of their current use of AI and the interpretation of data in the context of subject-specific frameworks.

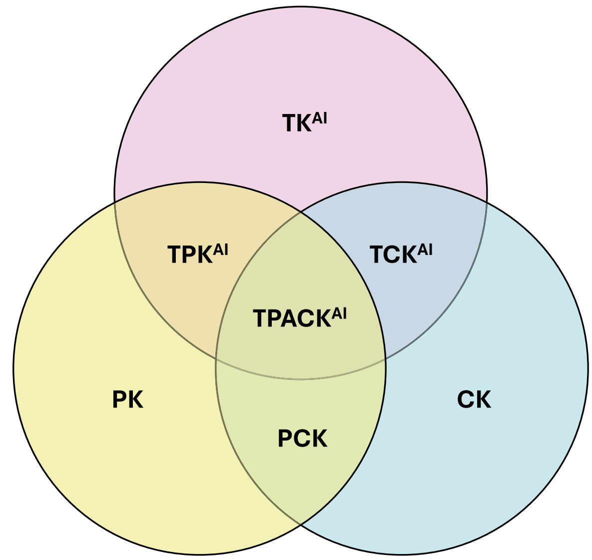

Fig. 1. TPACK model (according to Koehler et al. [33]) adapted for AI.

1.2.1. AI literacy

In line with the increasing socio-cultural integration of AI and the stated aim of helping citizens to become AI-literate (e.g. Vuorikari et al. [9]), it is possible that in-service teachers already have a certain level of general AI literacy. Such subject-unspecific AI literacy can be defined as "[…] a set of competencies that enable individuals to critically evaluate AI technologies, communicate and collaborate effectively with AI, and use AI as a tool online, at home and at work" ([34], p. 2). Validated competence tests (e.g. Hornberger et al. [35]) and self-assessment questionnaires (e.g. Laupichler et al. [36]) already exist to measure general AI literacy. The assessment of such subject-unspecific AI literacy provides indications about prior AI knowledge and, thus, whether and to what extent in-service teachers require post-qualification that addresses such literacy to use AI in their jobs.

1.2.2. AI usage

The areas of teaching in which teachers currently use AI could provide insight into how well-developed their skills in using AI in these areas of teaching are. If AI is used frequently (or rarely) in certain areas, this can serve as an indicator of existing (or lacking) AI competencies and thus provide guidance on designing post-qualification programs. However, a systematic study examining how teachers use AI in different areas of teaching in science education has yet to be conducted. As part of the DiKoLAN framework (an established framework in Germany and German-speaking parts of Europe), Kotzebue et al. [37] describe seven areas of teaching in the natural sciences: Within the framework, a distinction is made between the more subject-specific areas "Data Acquisition" (DAQ), "Data Processing" (DAP) and "Simulation and Modelling" (SIM), as well as the more general areas "Documentation" (DOC), "Presentation" (PRE), "Communication/Collaboration" (COM), "Information Search and Evaluation" (ISE) and the recently added area of "Assessment, Feedback, Adaptivity" (AFA; Thyssen et al. [38]).

Depending on the use of AI in certain areas of teaching in science education (according to DiKoLAN), insights can be gained into how post-qualification could be designed and where its focus should be placed.

1.3. Developing science educator's AI competencies

Based on which AI-related competencies in-service teachers already possess, the question arises of whether $TPACK^{AI}$ needs to be developed by in-service teachers and if so, how $TPACK^{AI}$ could be developed by them. If such professional development concepts are needed, they should be based on the existing competencies of in-service teachers [33].

Given their university education and professional experience, it can be assumed that in-service teachers already possess AI-independent teaching competencies (PK, PCK, and CK, according to the TPACK model). This should be considered when developing appropriate professional development concepts. Koehler et al. [33] have already established that "Research […] has not identified an ideal developmental sequence for developing TPACK" ([33], p. 106). Accordingly, the question arises as to which starting points should be chosen to develop $TPACK^{AI}$ among in-service teachers within the context of any post-qualification that might be necessary.

2. Rationale and research questions

To determine the necessity and scope of AI-related professional development programs for in-service teachers, it is crucial first to assess their existing AI competencies and understand the current role of AI in their lesson planning, implementation, and follow-up before developing such programs. This study aims to determine the extent to which in-service science educators in secondary education already have general AI literacy and how this relates to AI use. Further, the reasons for using AI and the purposes for which they use it in their teaching context in science education are to be investigated. It is also of interest to what extent this use is influenced by factors such as the subject taught or to what extent teachers see opportunities to use AI at all. Based on these findings, the aim is to be able to conclude a) the need for AI-related post-qualification offers and b), if necessary, adequate starting points and focal points for future post-qualification programs. Such qualifications should encourage science educators to use AI professionally in line with TPACK. The following research questions are therefore posed:

RQ1: What is the AI literacy level of secondary education in-service teachers?

RQ2: To what extent is the AI literacy of in-service teachers related to:

- AI use (usage history, frequency of use, and frequency of usage opportunities seen)
- Personal data (age, gender, years of service)

RQ3: What reasons do teachers report for deciding to use AI in class or for preparation and follow-up of lessons?

RQ4: In which areas (according to DiKoLAN) do in-service science educators use AI in class or for its preparation and follow-up?

RQ5: To what extent do teachers with different usage histories of AI differ in terms of the frequency of seen opportunities for use?

RQ6: To what extent is there a relation between the subjects and the use of AI in the classroom or for its preparation and follow-up?

3. Method, sample and data analyses

A cross-sectional mixed-methods design was employed. The quantitative part was based on an online survey of in-service secondary school science educators from Germany and Switzerland (n_{total} = 115), recruited via email invitations sent to randomly selected secondary schools (Baden-Wuerttemberg, Rhineland-Palatinate, North Rhine-Westphalia) and schools in Switzerland. A mixed methods approach consisting of three core elements was chosen to analyze the research questions:

(1) The teachers' AI literacy was assessed using a validated competency test by Hornberger et al. [35] consisting of 30 multiple-choice items. The test covers sixteen sub-competency areas of general AI literacy, including questions on how AI works, its weaknesses and strengths, as well as ethical aspects in the context of using AI. One point was awarded for each correctly answered item. In accordance with Hornberger's [35] recommendation, the test was carried out with 30 instead of the original 31 items.

(2) Additionally, the teachers' use of AI in class and its preparation and follow-up was recorded with a second questionnaire consisting of 15 items (see Appendix (App.) A). Participants had to check boxes when agreeing with a statement or indicate frequencies on five-point Likert-type scales (ranging from "never (0)" to "often (4)"). Data from (1) and (2) was collected online using the survey tool LimeSurvey.

(3) The third part of the study consisted of a semi-structured online interview in which teachers could participate voluntarily after they had completed parts (1) and (2). The interview intended to gain an in-depth insight into the information from (1) and (2). The interview questions can be found in App. B.

Teachers were only able to participate after agreeing to the data protection and consent form. Data was collected in 2024.

3.1. Sample

Germany and the German-speaking part of Switzerland were selected as the study sample in order to examine local conditions as well as the difference between German and Swiss teachers (who are not trained using digCompEdu (see Section 1.2)) to develop professional development programs for teachers in these regions. Teachers in active school service who were qualified to teach at least one science subject (biology, chemistry, or physics) were surveyed. Since a single teacher may teach up to three subjects (due to the German educational system), the number of subject-related data sets exceeds the number of participating teachers. The composition of the samples used to answer the respective research questions is shown in Fig. 2 and explained below.

The questionnaire was completed by n_{total} = 115 secondary school science educators from Germany and Switzerland. The participants were between 25 and 64 years old. As explained below, different sub-samples were formed to answer the respective research questions.

3.1.1. Samples for investigating RQ1 and RQ2

Analogous to the procedure described by Hornberger et al. [35], only data sets from participants with n_{total} = 115 who answered more than 75 % of the AI literacy questionnaire were included in the analysis for the AI literacy survey. This applies to $n_{literacy}$ = 64 people in the sample. Of these, 47 % (n = 30) are women, 50 % (n = 32) are men, and 3 % (n = 2) did not provide any information. To investigate the interdisciplinary

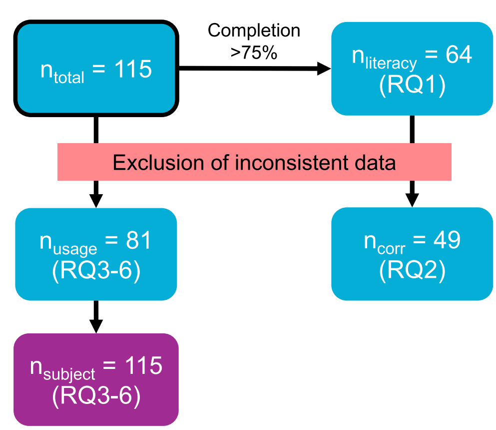

Fig. 2. Samples and the correspopnding research questions they address (number of teachers who: completed the questionnaire - n_{total}, completed the questionnaire properly - n_{usage}, completed the AI literacy test properly - $n_{literacy}$, completed both the questionnaire and the AI literacy test properly - n_{corr}, and number of subject-specific data sets - $n_{subject}$); blue: person-related data, purple: subject-specific data.

correlation between AI literacy and AI usage (analysis using IBM SPSS Statistics 30), the sample of those who completed more than 75 % of the AI literacy was further restricted by excluding inconsistent data (e.g., simultaneous indication of use and non-use). This left $n_{corr} = 49$ people, of whom 49 % ($n = 24$) are women, 47 % ($n = 23$) are men and 4 % ($n = 2$) did not provide any information about their gender.

3.1.2. Samples for investigating RQ3–6

Of the $n_{total} = 115$ participants, inconsistent data sets ($n = 34$) were excluded before the analysis resulting in a sample of $n_{usage} = 81$ teachers: 53 % ($n = 43$) are women, 44 % ($n = 36$) are men, $n = 2$ teachers (2 %) did not specify their gender. Forty-nine of them teach only one science subject ($n = 23$ biology, $n = 10$ chemistry, and $n = 16$ physics), while $n = 32$ teachers stated that they teach two or more science subjects. Since teachers in Germany are generally trained in at least two school subjects, the data were collected at the subject level. This resulted in a data set of $n_{subject} = 115$ (out of $n_{usage} = 81$ teachers) at the subject level, which were distributed as follows: $n = 44$ data sets for biology, $n = 39$ for chemistry, and $n = 32$ for physics. An analysis at the subject level was carried out for RQ3–6.

3.1.3. Sample for the interview

A total of $n = 21$ teachers ($n = 8$ female, $n = 13$ male; between the age of 28 and 57) who had fully completed both part 1 (AI literacy test) and part 2 (usage survey) of the online questionnaire agreed to participate in a semi-structured interview after completing the questionnaire.

3.2. Data analysis

A significance level of 5 % was set for all analyses. The chi-square test was used to calculate correlations of nominally scaled variables, and Phi or Cramer's V was determined. Depending on the sample size and degree of freedom, Fisher's exact test and Yates' correction were used if necessary. Differences between nominal- and ordinal-scale variables were calculated using the Kruskal-Wallis test and Mann-Whitney test, respectively. Correlations of two ordinal scales (or higher) were calculated according to Spearman. The eta coefficient was determined for dependencies between metric and nominal scales.

The AI literacy questionnaire was evaluated by awarding one point for each correctly answered item. A maximum of 30 points could be achieved. For AI literacy investigations, the teachers were divided by median split into the groups "AI-literate" (better AI literacy values) and "AI-illiterate" (worse AI literacy values). The post-questionnaire interviews were prepared and conducted following the principles of Mayring and Fenzl [39]. To analyze the interviews, teachers' responses to the questions of the semi-structured interviews were grouped into inductive categories using a consensus coding approach [40]. Two coders independently derived initial categories from the data, which were subsequently compared, discussed, and refined collaboratively to arrive at a shared set of categories (see App. C).

4. Findings

4.1. AI literacy of in-service science educators (RQ1)

The results of the valid literacy tests ($n_{\text{literacy}} = 64$) show that participants achieved a mean score of 16.7 points ($SD = 4.59$) out of a maximum possible 30 points.

4.2. Correlation of AI use and personal data with AI literacy (RQ2)

The history of AI use ("current AI use", "AI use for some time (for at least six months)", "never used AI", and "AI is not being used anymore") was investigated regarding its correlation with AI literacy. No significant correlations (all p-values between 0.109 and 1.00) were found between AI-literate and AI-illiterate teachers regarding their AI usage history. Thus, no influence of AI literacy on the history of AI usage could be proven.

The study also investigated how frequently teachers see opportunities to use AI and how this frequency is related to AI literacy. There was also no significant difference between AI-literate and AI-illiterate teachers in terms of the average frequency of AI usage opportunities seen in class ($p = .151$) or for lesson preparation and follow-up ($p = .947$). Consequently, how often teachers see opportunities to use AI is independent of their AI literacy.

In summary, AI literacy is not related to the decision to use AI in the school context. In addition to usage history, correlations between AI literacy and age, gender, and years of service were examined. None of these factors were found to be significantly related to AI literacy (all p between 0.333 and 0.462). This indicates that general AI literacy among the teachers surveyed is independent of age, gender, and teaching experience. A complete list of all calculated values can be found in App. D.

4.3. Reasons for decisions regarding AI use (RQ3)

The subject-specific data sets ($n_{subject} = 115$) were analyzed to determine which reasons were given most frequently and least frequently for their decision to use AI in the science subjects. "Fun or interest" in using AI in class was given $n = 47$ times in total as a reason for the decision, making it the most frequently selected reason. The least relevant reason for the decision to use AI in class is "… because I have noticed that AI is used as a research method in the science discipline and is, therefore, part of the subject I teach". This item was selected $n = 17$ times in total. Regarding the use of AI in lesson preparation and follow-up, the most common reasons were saving time ($n = 63$) and the importance of considering this new technological development ($n = 62$). An overview of the reasons for using AI in class, preparation, and follow-up work is given in Fig. 3.

The most common reason given in total for why AI had not yet been used in class was that teachers "have not (yet) dealt with it" ($n = 34$). The most common reason given for not using AI for preparation and follow-up was the lack of free access to AI tools ($n = 21$). The most common reasons AI is not used in class anymore are the lack of free access ($n = 10$) and teachers considering it too time-consuming ($n = 10$). This consideration was also the most common reason AI is no longer used for the preparation and follow-up of lessons ($n = 9$). For more information on the reasons for AI use, see App. D.

4.4. Areas of AI use (RQ4)

A survey was conducted to determine in which subject-specific scenarios/areas (as defined in DiKoLAN) teachers use AI, distinguishing between its use in the classroom and its use for lesson preparation and follow-up. Fig. 4 shows the cross-curricular use of AI in class (left) and for lesson preparation and follow-up (right).

In class, AI is being used most frequently in the ISE area ($n = 43$ times in class, $n = 53$ times for lesson preparation and follow-up). AI is used least frequently in the area of DAQ - both in class ($n = 7$) and for lesson preparation and follow-up ($n = 11$). AI also plays a comparatively important role in lesson preparation and follow-up in the areas of AFA ($n = 41$) and PRE ($n = 31$). The use of AI in the classroom in these areas is less distinct. Overall, AI is used much less frequently on average in the more subject-specific areas (SIM, DAP, DAQ; $M = 15$ mentions) than in the more general areas (COM, PRE, ISE, DOC, AFA; $M = 28.8$ mentions).

4.5. Seen opportunities to use AI (RQ5)

The data analysis shows that participating teachers who see opportunities to use AI more frequently also use it significantly more often (see Table 1).

Similarly, teachers who have been using AI for an extended duration

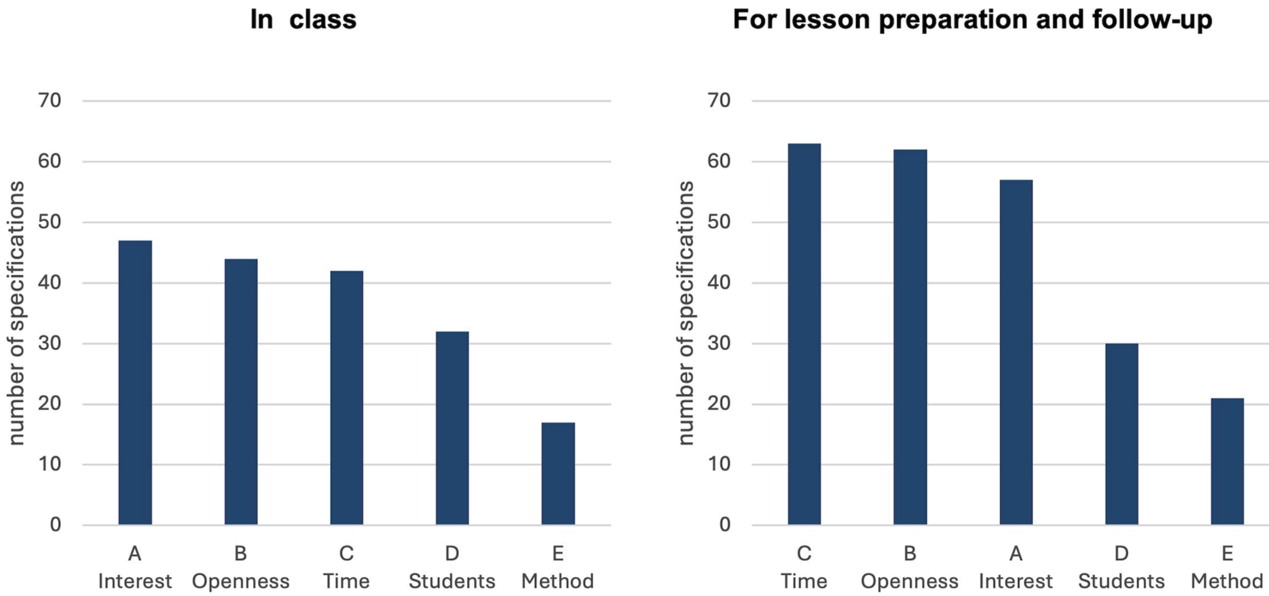

Fig. 3. Reasons for using AI in class (left) and to prepare and follow up lessons (right): A) I enjoy/am interested in AI, B) openness to technology, C) timesaving, D) Students use AI/want to use AI, E) AI is a method of scientific research and therefore part of my subject.

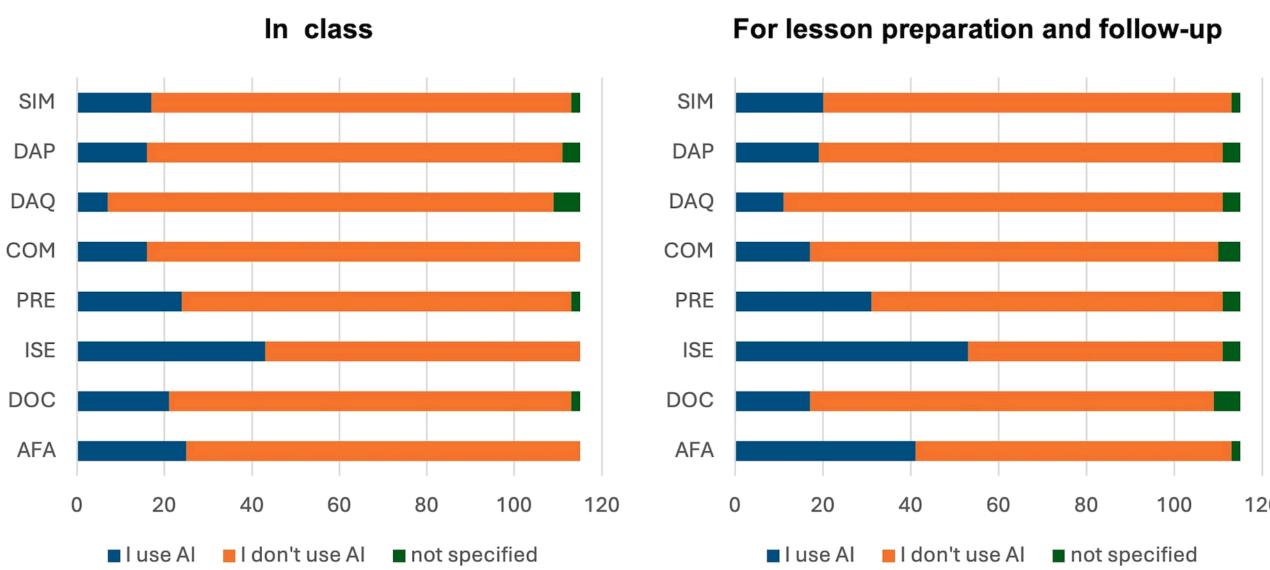

Fig. 4. Areas of AI usage in class (left) and for lesson preparation and follow-up (right): simulation and modelling (SIM); data processing (DAP); data acquisition (DAQ); communication/collaboration (COM); presentation (PRE); information search and evaluation (ISE); documentation (DOC); assessment, feedback, adaptivity (AFA).

Table 1
Correlations of current AI usage with the average frequencies of perceived opportunities to use AI.

Current AI usage	The average frequency with which opportunities to use AI are seen	*n*	r	p
In class	In class	110	.45	<0.001
In class	For the preparation and follow-up of lessons	113	.32	<0.001
For the preparation and follow-up of lessons	In class	111	.33	<0.001
For the preparation and follow-up of lessons	For the preparation and follow-up of lessons	115	.58	<0.001

are significantly more likely to see opportunities to use it. Teachers who have been using AI in the classroom for a longer period do not see opportunities for use in lesson preparation and follow-up significantly more often than teachers with other usage histories. The calculated values of all investigated differences are listed in App. F.

4.6. Usage of AI and its correlation with science subjects (RQ6)

At the subject level ($n_{subject} = 115$ data sets), various aspects of AI use were analyzed, such as the history of use, the frequency of seen opportunities for use, the areas of use, and the reasons for the decision to use AI: 63 % of this data stated that AI was currently used for preparation and follow-up of classes (Fig. 5, right), while only 43 % of all data stated that AI was currently used in class (Fig. 5, left).

The analysis showed (with one exception) no significant correlations

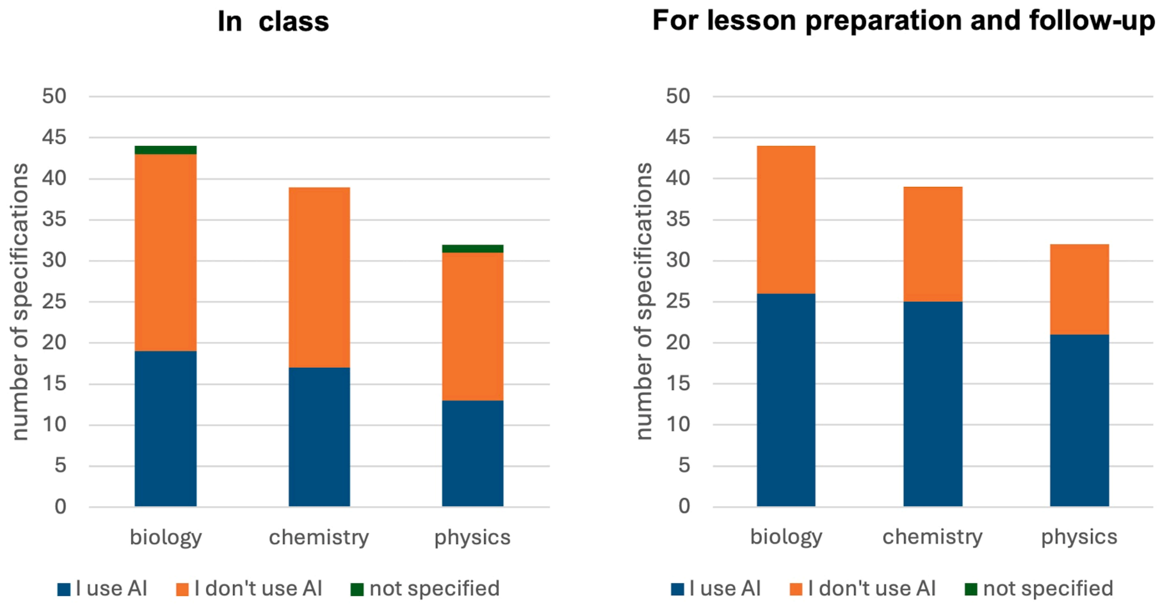

Fig. 5. Number of specifications on whether AI is used or not used in class (left) and for the preparation and follow-up of lessons (right) by subject.

(all p between 0.062 and 1) between the different subject disciplines and the investigated aspects of AI use (see App. G). The only significant correlation was found in the item "I have never used AI for lesson preparation and follow-up because there is no subject-specific relevance" ($n = 106$, Cramer's $V = 0.437$, $p_{\text{Fisher}} = <0.001$). This reason why AI has not been used in class before was mentioned most frequently ($n = 12$) for chemistry. In summary, however, the use of AI is predominantly independent of the science subject taught.

4.7. Post-questionnaire interviews

In the post-questionnaire interviews, $n = 21$ participants were asked to explain and indicate what opportunities they see for using AI in a school context, identify the challenges they perceive regarding the use of AI in school, and suggest topics they consider essential for future AI-related professional development programs (see App. B).

Overall, out of the $n = 21$ interviewed teachers only $n = 12$ stated that they already used AI in class or are currently using it in class. The most frequently mentioned AI use during class, with $n = 7$ responses, was the use of AI by students conducting their own research with the help of AI ("research conducted by students"). Some of these teachers described that the use of AI for research in class underlies certain guidelines:

> "*In class, I like to do it this way: when the students […] have search tasks […] or […] research tasks, then they're welcome to use AI, but I always tell them […] that they should then explain it to us so that we can understand it without using technical terms […]" (interview 10, translated from German).*

Regarding perceived opportunities for using AI in a school setting, respondents most frequently cited the possibility of using AI for adaptive purposes ("adaptivity") ($n = 8$). Among these, several possibilities were listed, such as the linguistic differentiation of tasks and texts based on both the proficiency level and the students' respective native languages. However, feedback mechanisms and chatbot interactions were also cited as potential applications for adaptive use. At the same time, teachers saw high potential in the "creation of teaching material" ($n = 7$) and in supporting "lesson planning" ($n = 5$) with the help of AI. Regarding the obstacles teachers perceive in using AI, the most frequently cited issues fell into the categories of insufficient "output quality" of AI and concerns about a decline in students' cognitive engagement when AI is used as a tool in the classroom ("lack of cognitive ability") ($n = 9$ each). For example, they expressed the concern that:

> *"[…], students' thinking skills will decline. They enter the question […], get the answer, and read it aloud" (interview 8, translated from German)*

Another important obstacle in using AI mentioned by the teachers was their own lack of engagement and thus a lack of competencies for the effective integration of AI into the classroom ("lack of engagement/competencies (on the part of teachers)") as well as the challenge of not having free access to AI tools ("costs") ($n = 7$ each). Regarding professional development, most teachers explicitly emphasized the importance of subject-specific examples for the application of AI ("specific examples of use") ($n = 11$), followed by an overview of general application possibilities for AI ("general use") ($n = 7$) as the two most relevant topics. Among other things, a need was also expressed for content related to "time savings" ($n = 6$) and "legal frameworks" ($n = 5$). A complete overview of the coded responses can be found in App. C.

5. Discussion and implications

This study aims to determine whether there is a need for AI-related post-qualification for in-service teachers and, if so, where it could begin. The results clearly suggest that such post-qualification is needed.

This is shown on the one hand by the distribution of usage areas concerning the DiKoLAN areas; it is noticeable that AI is used much less frequently on average in the more subject-specific DiKoLAN areas (SIM, DAP, DAQ) compared to the more general areas. In line with this finding, AI is being used subject-independent. The difference in use between subject-specific and more general areas could indicate teachers' limited knowledge of how AI can be used in subject-specific areas. By contrasting the rarely specified AI areas of use with the DiKoLAN$^{\text{AI}}$ framework [41], it is possible to identify which AI competencies should be specifically addressed in post-qualification programs. A few such DiKoLAN$^{\text{AI}}$-related programs already exist in this regard [42]. These programs need to be tested and researched to assess their impact. It should also be noted that the use of AI is particularly focused on ISE, AFA, and PRE, which is further supported by the post-survey interviews. In response to the survey on the use of AI, teachers reported between other things the following:

> *"[I used AI] almost exclusively for research purposes" (interview 9, translated from German)*

"[my students] used the AI a little bit, created some images […] and then put together a cute little comic" (interview 15, translated from German).

In addition, the literature contains many references to the use of AI in the context of adaptivity (AFA) for example to generate (differentiated) learning materials [43,17] or tests to record and evaluate student performance [19,23]. The generally weaker use of AI in the classroom especially in the area of AFA - compared to the use for lesson preparation and follow-up - suggests that the teachers surveyed are not aware of AI-based applications for automated adaptive teaching, such as intelligent tutoring systems (ITS) and tutorbots [44,45]. However, the results of the interviews also show that teachers tend to be cautious about using AI in the classroom, and when they do, they mostly use it for research tasks (ISE). Above all, it is also evident in the interviews that the requests regarding professional development opportunities focus not only on the general potential uses of AI but also explicitly call for examples of (subject-specific) use cases.

"And then there's actually the subject-specific stuff, that's what really needs to be done more. Because when it comes to AI in general, I know just a tiny bit about it. But I think that, especially in subjects involving simulation or whatever, it could be used much more […]" (interview 5, translated from German).

As emphasized for pre-service teachers by Tondeur et al. [46], post-qualification programs for in-service teachers should not be conceived as a stand-alone offer detached from subject-specific and educational contexts, too. Instead, such programs should be designed as an integrated component of the school context and the respective subject.

In addition, the need for AI-related post-qualification is evident from teachers' reported reasons for AI use and non-use: For many teachers, an important reason for use - saving time in lesson preparation and follow-up (also found by Hashem et al. [47] and Labadze et al. [22]) - could serve as an opening argument for use. This aspect also emerged in the interviews, where participants emphasized that post-qualification should specifically address how AI can be used to save time in everyday teaching practice and preparation. Frequently cited reasons for not using AI regarding the questionnaire are: the lack of engagement with the technology, no perceived benefits from its use, and the lack of free access to AI tools. In the interviews, the teachers surveyed also stated that a lack of personal competencies (due to the fact that they had not yet dealt with AI sufficiently) was an obstacle to the use of AI in school. Accordingly, post-qualification offers must be developed to show teachers the potential for AI use (possibly subject-specific). With regard to the stated lack of access to AI tools, there is also a need for action by the responsible departments to make these available, thereby making it easier for teachers to take their first steps in using AI.

Furthermore, the relevance of AI in the natural sciences is rarely mentioned by in-service teachers as a reason for using AI as a learning subject. A lack of knowledge about the scientific significance of AI, its applications in science, and how this could be addressed in science lessons can be assumed here. A look at the (significantly positive) correlation between the frequency of perceived opportunities for use and the actual AI use also implies a general need to show teachers possibilities and opportunities for using AI in their subject. As the analysis of the interviews indicates, it is particularly interesting for teachers to learn how AI can be used, for example, to adapt lesson design or create teaching materials. In summary, a need for post-qualification courses for in-service science educators can be formulated so that they can engage with different ways of using AI. In particular, the promotion of subject-specific AI skills and the identification of (subject-specific) opportunities for use appear to be necessary focal points of these post-qualification courses within the context of the findings of this study.

Possible starting points for such courses can be derived from the insights into the general AI literacy of the in-service teachers surveyed. To do so, the AI literacy values surveyed must first be compared with the findings of Hornberger et al. [35], and correlations with the teachers' AI use must be considered. Table 2 shows a comparison of the sample sizes (n), item count (n_i), mean values (M), and standard deviations (SD).

In addition to the significantly higher sample size, it is noticeable that the literacy score mean and standard deviation measured by Hornberger et al. [35] are higher. These values were calculated on the basis of the results of the original questionnaire comprising 31 items. Item 7 was subsequently removed from this questionnaire due to its poor discrimination parameter [35]. Accordingly, the current survey was conducted using the updated questionnaire, which now only contained 30 items. Furthermore, the samples of both studies differ in their composition; Hornberger et al. [35] surveyed the AI literacy of university students, which represent an, on average, younger and less diversified group (in terms of age) than the teachers surveyed. Overall, the students are predominantly from mathematical-technical and scientific degree programs (a total of 62.0 % of the total sample). It can be assumed that students in such courses have higher AI literacy due to the course content [48,49]. Approximately one-fifth (19.6 %) of the students in the Hornberger et al. [35] sample reported having already attended lectures on AI. In this context, the AI literacy of in-service science educators can be rated as comparatively good or at least similar to the students' literacy.

Based on the definition of AI literacy underlying the questionnaire used [34], AI literacy can be classified as TK^{AI} and TPK^{AI} due to the technological and social focus and the lack of subject orientation in the sense of TPACK. Furthermore, given their training and professional experience, it can be assumed that in-service teachers possess PK, PCK, and CK. In view of the implicit integration of undefined AI competencies in frameworks such as TPACK, it is unclear if in-service teachers possess AI competencies such as TPK^{AI}, TK^{AI}, and TCK^{AI}. However, the evaluation of the literacy tests indicates the presence of TPK^{AI} and TK^{AI} among in-service teachers.

The results regarding the investigated correlations between AI literacy and aspects of AI use impressively show that general, subject-unspecific AI literacy plays no role in the decision to use AI in the classroom or for its preparation and follow-up. One important reason for this absence of correlation is certainly the (partial) lack of access to AI tools for teachers. At the same time, it must also be taken into account that the AI literacy test used only assesses general knowledge about AI. According to the information provided by the teachers surveyed regarding their previous experience with school- and subject-specific applications of AI and their self-perceived AI competencies, teachers lack school- and subject-specific knowledge about AI. This knowledge gap could be another reason for the absence of a correlation between AI literacy and AI use. In this context, future research should examine whether general AI literacy (TK^{AI} and TPK^{AI}) for teachers needs to be adapted to also cover school- and science-specific AI competencies (TCK^{AI} and $TPACK^{AI}$) and whether this has a positive influence on the use of AI by in-service science educators. This also raises the question of how TCK^{AI} and $TPACK^{AI}$ could be promoted among in-service teachers to help them use AI more efficiently. In the context of the findings of this study, AI-related post-qualification courses for in-service science educators should be as subject-specific as possible, which is why we propose two paths for the development of $TPACK^{AI}$ (see Fig. 6):

Path A: Pedagogical Content Knowledge (PCK) represents a teacher's knowledge of preparing the subject matter for students and supporting

Table 2
Sample size (n), item count (n_i), mean (M), and standard deviation (SD) of the AI literacy scores of the current study compared with Hornberger et al. [35].

Value	Current study	Hornberger et al.
n	64	1286
n_i	30	31
M	16,70	18,79
SD	4,59	5,57

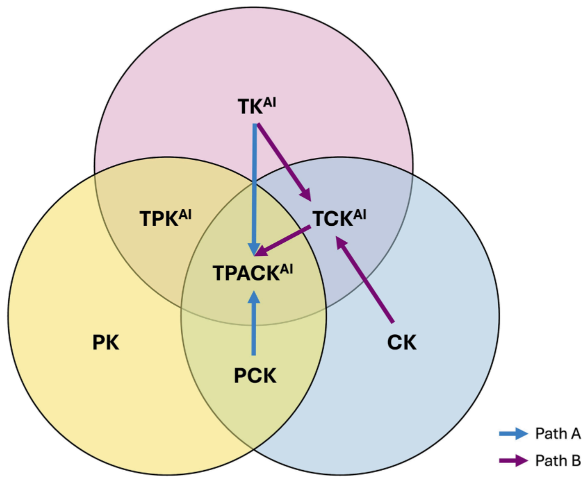

Fig. 6. TPACK model (according to Koehler et al. [33]) adapted for AI with possible pathways to support the development of TPACK^{AI} among in-service teachers.

their subsequent learning [27]. The enrichment of this didactic knowledge with technological (AI-related) knowledge (TK^{AI}) leads to TPACK^{AI} and can thus enable teachers to use AI efficiently as a tool for the preparation and follow-up of lessons as well as for the individualized support of individual learners.

Path B: Given the vast and continually growing importance of AI across scientific disciplines, it is necessary to equip science educators with knowledge of AI's role in the science subjects they teach (TCK^{AI}). Combining this TCK^{AI} with existing didactic knowledge (PCK) enables teachers to develop TPACK^{AI} and thus use AI as a subject matter. In this way, pupils can gain insight into modern AI-driven science to inspire and prepare them for future educational and career paths in science.

It should be noted at this point that the limitations of the TPACK model with regard to generative AI (highlighted by Mishra et al. [50]) must be taken into account. According to Mishra et al. [50], while the TPACK model remains relevant as a foundation for the effective use of various digital technologies, it needs to be extended to meet the unique requirements of generative AI. An extension of the purely technical consideration of technology to include socio-cultural and ethical aspects, as already proposed in the DPACK model [51], is particularly necessary for the context of AI and should be integrated into AI-related teacher training [50]. More research is needed to understand what role school- and science-specific AI literacy (TCK^{AI} and TPACK^{AI}) plays in-service teachers' use of AI and how such literacy can be promoted best. Follow-up surveys on the use of AI by in-service science educators can also provide valuable insights into possible changes in areas of use and reasons for use, caused, for example, by attending post-qualification courses, the technical progress of AI systems, or improved access to AI tools. Taken together, the findings suggest that the absence of a relationship between general AI literacy and AI use can be attributed to three interrelated factors: limited pedagogical integration of AI in subject-specific contexts, insufficient contextualized professional development for science educators, and restricted access to suitable AI infrastructure in schools.

6. Limitations

One possible bias of this study is that, due to the self-selection of participants for the survey and interview, teachers interested in AI may have participated more frequently in the survey. The results may have been influenced accordingly, for example, concerning the proportion of teachers using AI (self-selection bias [52]). On the other hand, the small sample size could have masked possible correlations, for example, in the aspects "use of AI for a long time" and "discontinued use of AI". It should also be noted that the teachers surveyed were not given a definition of AI or descriptions of the individual areas of AI use. It can, therefore, not be assumed with certainty that all participants understood the items in the same way. In addition, no questions were asked as to whether AI had already been discussed in the past in post-qualification courses or even during studies. Consequently, it is difficult to draw conclusions about the current level of knowledge of in-service teachers concerning possible areas of AI use. This study was also subject to limitations with regard to the classification of the teachers' measured AI literacy. A direct comparison of the results of the AI literacy test with the data collected by Hornberger et al. [35] is difficult due to the different maximum scores and the different sample composition.

7. Conclusion

This study examined the extent to which in-service science educators use AI for lesson preparation and follow-up as well as in the classroom, their reasons for or against the use of AI, what general AI literacy these teachers possess, and to what extent this is related to their use of AI. The aim of this study was to find indications as to whether there is a need for AI-related post-qualification courses and where such post-qualification could possibly start. The results of the study confirm the need of such courses. Although in-service science educators have general AI literacy, no correlation was found between their use of AI and their AI literacy. Given the reported AI usage areas, AI-related post-qualification courses should focus on promoting school- and subject-specific AI literacy and highlighting concrete subject-specific usage opportunities. In order to enable in-service teachers to use AI efficiently as a tool or subject in science lessons within such post-qualification, we propose two pathways for developing TPACK^{AI}. However, further research is needed to test these pathways and the role of subject-specific AI literacy in teachers' AI use. In this context, the specific competencies involved in such literacy must also be defined. Nevertheless, this study provides important evidence for the development of AI-related post-qualification courses for in-service science educators.

Declaration of generative AI and AI-assisted technologies in the writing process

During the preparation of this work, the authors used DeepL to check translations and ChatGPT to improve readability and refine formulations. After using these tools/services, the authors reviewed and edited the content as needed and take full responsibility for the content of the publication.

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CRediT authorship contribution statement

Nikolai Maurer: Writing – original draft, Visualization, Validation, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Mathea Brückner:** Writing – original draft, Visualization, Validation, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Christoph Thyssen:** Writing – review & editing, Supervision, Project administration, Methodology, Conceptualization. **Sebastian Becker-Genschow:** Writing – review & editing, Supervision, Methodology, Conceptualization. **Johannes Huwer:** Writing – review & editing, Supervision, Resources, Project administration, Funding acquisition, Conceptualization.

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.

Supplementary materials

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.caeo.2026.100376.

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