Artificial Intelligence in Compulsory K-12 Computer Science Classrooms: A Scalable Professional Development Offer for Computer Science Teachers

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ABSTRACT

Given the ever-growing importance of artificial intelligence in our society and daily lives, everyone needs to learn about the core ideas and principles of this technology. While there is still a lack of empirical findings on the teaching and learning about AI in K-12 education, various teaching approaches and materials have been developed in recent years, and the topic is being introduced into K-12 computer science curricula. However, qualifying CS teachers to adequately teach this new field is a significant challenge, as they require extensive content knowledge as well as pedagogical content knowledge. In this paper, we describe the conditions and challenges and the resulting design of a professional development offer to prepare teachers for the introduction of AI into mandatory K-12 CS education in Bavaria (Germany). By designing a scalable PD program in a blended learning format and building on principles such as the "pedagogical double-decker", we successfully addressed challenges such as limited resources, a large number of teachers to be trained, and the significant heterogeneity of teachers' backgrounds. We also share the results of a formal evaluation and other lessons learned from the initial implementations, which contribute to the design of professional development for this pressing issue.

CCS CONCEPTS

• **Social and professional topics → K-12 education**.

KEYWORDS

artificial intelligence, professional development, computer science education, K-12, teacher education

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1 INTRODUCTION

Artificial intelligence (AI) has become an integral part of our world, and students are constantly confronted with AI-related phenomena and technology in their daily lives. To educate responsible citizens who can use AI confidently and responsibly, learning about this topic, its core ideas, limits and possibilities as early as in K-12 education is inevitable [35]. Various demands call for just this. At the international level, for example, UNESCO states that AI has fundamentally changed the world and therefore suggests that AI be included in curricula. Based on their analysis of government-endorsed AI syllabi, they point out that resource development and teacher professional development (PD) are essential for implementing AI in curricula [37, 38]. Similarly, on a national level, the German Association for Computer Science calls for integrating AI into CS curricula of all types of schools on a mandatory basis [10].

Like many other countries and educational systems, the German federal state of Bavaria has lately implemented those demands by introducing AI into CS curricula. Computer science as a subject was already mandatory for some of the students in high school ('Gymnasium') for almost twenty years [9]. Recently, additional compulsory computer science lessons were anchored for all students in year 11. AI takes up about a quarter of this grade‘s new mandatory computer science lessons. Therefore, unlike an elective class, not only particularly interested or motivated students, but everyone will learn about this topic. In addition, AI will be revisited in depth in (elective) year 13.

However, AI represents a largely new subject area for the K-12 classroom, which is still being developed in computing education research [24, 35]. Furthermore, teachers lack the necessary content knowledge and pedagogical content knowledge [16]. In order to prepare in-service computer science teachers for this new content area and to support them in designing action-oriented and motivating lessons, we have developed a PD offer. In this paper, after discussing related work, we report on the corresponding challenges and conditions (section 3), the resulting design of the PD (section 4), as well as our experiences and results (section 5).

2 RELATED WORK

In the last years, an ever-growing number of curricular initiatives (e.g., [15, 36]) as well as teaching concepts, materials, and tools for the classroom [5, 27, 41] for AI in K-12 education were developed. However, to successfully incorporate this new topic in the classroom, teachers must also be qualified. Professional development aims to expand teachers' professional competence, in particular cognitive (i.e., PCK according to Shulman [32]), motivational and personal components [1]. Given the dynamic scientific discipline, professional development, e.g., concerning new topics, new methods, or tools, is a common and essential part of CS teachers' profession.

Extensive research was conducted on the design of PD for teachers within (e.g., [7, 21, 28, 29]) and beyond computing education (e.g., [2, 3, 6, 12, 18]) in various formats. The respective results emphasize principles such as self-directed and active learning, working with classroom-ready and -tested materials to support transfer, collaboration between the participants, a reasonable duration, or interchanging between input, experimentation, and reflective components for effective PD.

However, designing a successful PD offer is highly dependent on the content and context [18] – especially for a topic such as AI, where teachers typically lack content knowledge as well as any teaching experience in the classroom. In the following, we show the significant heterogeneity of existing PD offers on AI and summarize their main experiences and findings.

Some PD offers are targeting STEM and STEAM teachers. For example, Williams et al. [40] conducted a PD workshop for a particular AI and ethics curriculum, focusing mainly on the content of the specific intervention in the classroom. Similarly, Lee and Perret [13] report on a five-day PD focusing on data science and machine learning in STEM subjects. Among other things, they found technical challenges with the tools used and emphasized the integration of material directly applicable in the classroom.

Furthermore, Lee et al. [14] conducted a 20-hour PD in a book club format during the pandemic. From the experiences with STEM and CS teachers, among other things, they conclude the importance of collaboration to foster a community of practice. Kandlhofer et al. [11] also developed training modules targeting secondary students and teachers with and without prior CS experience. In three to five days, content knowledge on machine learning but also knowledge-based approaches such as reasoning and planning are conveyed. In particular, the participants highlighted the blended learning format.

Considering PD solely for CS teachers, Vazhayil et al. [39] report on a two-day PD offer focusing on machine learning with Indian CS teachers. Their results emphasize the importance of room for exploration to foster teachers' self-efficacy in this new field. Furthermore, Sun et al. [34] investigated a 25-day intervention to promote content knowledge and the teaching competency of Chinese K-12 computer science teachers. The PD format was based on the TPACK model and conducted in a blended learning format, which the authors considered successful.

In summary, there are significant differences between the various contexts and formats, e.g., duration, target group, terms of teacher training, teacher and student prerequisites, educational systems, particular curricula, and so on. So far, there is a lack of theoretically and empirically founded findings concerning design principles for PD, specifically for AI as a "new" topic in computing education [30]. With our approach, we are providing valuable experiences from an intensive PD offer: As far as we know, no report for such a broad and structured PD exists, that can be almost equated with an education program for teachers. For this purpose, we have applied general design principles for PD outlined above and transferred them to the field of AI, facing various context-specific challenges.

3 CONDITIONS AND CHALLENGES

In this section, we will describe the situation for K-12 CS education in Bavaria to lay out the resulting conditions and challenges for designing a PD offer.

Since 2003, computer science lessons have been mandatory in year 6 and 7 of the Bavarian high school ('Gymnasium'). Beginning in year 8, students can choose a branch within their high school education that fosters their interests and talents. In the science and technology branch, computer science is also mandatory in year 9 and 10, with two hours a week each. For students in other branches, there are no further lessons in computer science. With the start of the school year 2023/24, computer science is compulsory for all students in year 11 in all branches. In this process, AI as a topic was firmly anchored in year 11 (mandatory for all) and in year 13 (elective, from 25/26).

For the AI-related parts of the curriculum in year 11 (see Table 1), there are two variants, depending on whether the students already took computer science as a subject in the two years before or not ("late-start"). Contents are the discussion of possible definitions, fundamental ideas, as well as chances and risks of AI. Furthermore, a particular machine learning algorithm (optionally k-nearest neighbors or decision tree learning) will be explained and applied, and a single artificial neuron will be implemented (late-start: simulated). In year 13, among other things, knowledge-based systems will be implemented and applied. In addition, neural networks, together with forward propagation, will be introduced. The k-Means algorithm is presented, and a problem is implemented with a machine learning method[1].

Teachers who undergo regular teacher education in Bavaria are generally very well trained and have essential competencies for good teaching, both professionally and pedagogically. In Germany, education (including teacher education) is a matter of the federal states. Although there are many differences, the principles of the teacher education system are the same throughout Germany, and most of the following remarks can be applied to other federal states as well. Professional training of teachers in Bavaria takes place in two phases. In the first phase, they study in depth (usually five years) two teaching subjects as well as educational science (pedagogy and psychology) at a university. Building upon Shulman's PCK model [32], the studies in educational science address pedagogical knowledge, while the studies in the teaching subjects include both content knowledge as well as pedagogical content knowledge. After completing the first phase of education at university by passing a central examination, the second phase begins. For two years, each teacher goes through a preparatory service at school. The aim is to deepen their specialized pedagogical training and to gain teaching experience. The second phase also ends with an examination. It mainly addresses curriculum and pedagogical content knowledge.

However, the majority of Bavarian computer science teachers have not completed a basic computer science teaching degree, but

[1] https://www.lehrplanplus.bayern.de/ (German only)

Table 1: Learning Objectives in the Bavarian Curriculum on AI (year 11)

Students discuss approaches to defining the term artificial intelligence (AI), describe various basic ideas of AI methods (including machine learning) and their areas of application.
Students explain the functionality of a selected machine learning algorithm (k-nearest neighbors or decision tree learning) in general and for concrete examples.
Students analyze the influence of training data and parameters on the reliability of the results of a machine learning procedure, if necessary using a suitable tool.
Students explain the functionality of an artificial neuron (perceptron) and describe the basic structure of a neural network.
Students implement (late start: simulate) a single artificial neuron.
Students take a position on selected current possible applications of artificial intelligence and evaluate opportunities and risks for the individual and society.

only a heavily shortened *extension study* [23]. Due to the great shortage of computer science teachers, there have been several offers in recent years to become a computer science teacher without having to go through a full degree program. For example, in-service teachers from other disciplines could complete their computer science studies (with a limited scope) in two years while working.

AI has not been part of the teacher training program so far (neither in regular education or in a shortened study). Thus, on the one hand, **little prior experience** on the subject of AI can be assumed (see for example also [16]). However, some teachers may already have familiarized themselves with the subject on their own. On the other hand, an overall **great heterogeneity** is to be expected regarding further computer science basics and teaching experience in computer science classes.

In addition to the heterogeneity of the teachers due to the different educational backgrounds, there were further challenges in the conception of the PD. One challenge was the number of teachers to be trained. In the regionally widely spread catchment area of the TU Munich, there are about 450 K-12 computer science teachers. With a lead time of just over a year and **limited personnel resources**, a scalable format (e.g., with extensive self-learning phases) seems central to providing a PD offer for most teachers. At the same time, personal networking among teachers in the sense of a **community of practice** is particularly important for this new topic, which would be fostered by having on-site components in the PD offer.

Due to the extensive content to be taught and to avoid teachers being confronted with knowledge that cannot be elaborated as it can only be applied in a few years, we have decided on a spiral curricular division into a basic PD offer (basics, year 11) and an advanced PD offer (deepening, year 13). The latter only begins in school year 24/25, is relevant for a much smaller group of teachers, and can build on their initial teaching experience on the topic. The basic PD offer aims to provide teachers with both basic content and pedagogical content knowledge as well as to consider the specific requirements of the curriculum. The following description refers only to this basic PD.

4 DESIGN OF THE PD OFFER

To design the content of the PD offer, we first outlined the intended learning outcomes. In order to implement the curriculum competently, teachers need a broad overview of the topic of AI and competencies that go beyond those listed in the curriculum. To derive our learning objectives, we first analyzed existing approaches to structure the subject area from an educational perspective [19, 24, 35]. In this way, we could define a corpus of core competencies. We compared these with the curriculum, included further aspects, and set priorities according to the curriculum. After formulating the intended learning outcomes for the PD in this way, we grouped them with headings for a better overview (see Table 2). Furthermore, we designed an advance organizer (AO) that covers all topics of AI and supports structuring this broad area.

Table 2: Groups of the learning objectives derived for the PD

Definition and historical context of AI, strong vs. weak AI
AI problems, technologies and systems
Different approaches of AI
Concrete methods of machine learning
Influence of training data and hyperparameters on the reliability of the results of selected machine learning algorithms
Opportunities and risks for individuals and society

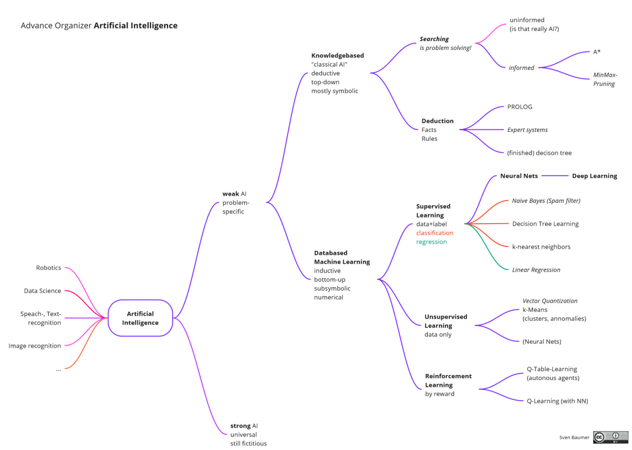

Figure 1: Advance Organizer for teachers in the PD

The design of the PD was based on the need for scalability in terms of time and resources as well as other requirements for successful PD programs known from the literature as outlined in section 2. In order to ensure personal networking among teachers while maintaining scalability, we opted for a blended learning format (see Figure 3). The core of the offer is the massive open online course (MOOC) "Exploring the World of AI"[2], which was already developed in 2021 by one of the authors and aims at the interested general public. By analyzing the content of the MOOC, we found that it already covers a large part of our intended learning outcomes. Therefore, we consider it well suited for an overview-like introduction to the topic. The MOOC was originally designed for three weeks, each containing four units. Each unit consists of a video (approximately 15 minutes), a subsequent self-test, and a more detailed hands-on task to review and deepen the content (such as implementing particular machine learning projects in Snap! [25]). The MOOC covers content such as attempts to define AI, an overview of knowledge-based approaches of AI, the different types of machine learning, insight into neural networks, and AI, ethics and our society. To take into account that teachers participate in the PD alongside their regular workload, they had approximately a span of six weeks to complete the MOOC. It can be done individually and at the participants' pace and scope to help us address the challenge of heterogeneous previous knowledge.

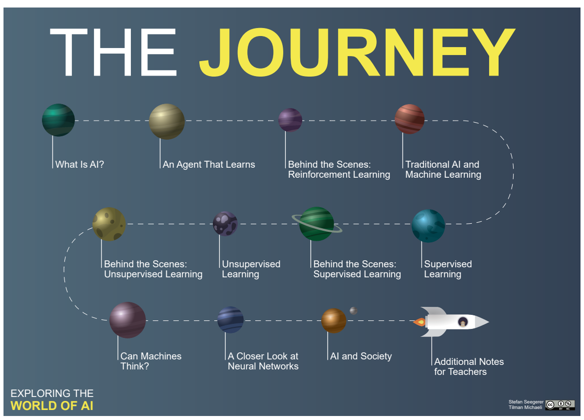

Figure 2: MOOC content and structure

Figure 3: Structure of the PD offer

The MOOC is framed by two on-site days at our university (duration of three and six hours, respectively). The first on-site day before starting the MOOC serves to network the participants with each other and to deepen their interest in the topic. To this end, a general overview of AI (using the AO) and the the curriculum requirements is given. Further, we use many playful approaches such as [17] in the sense of the "pedagogical double-decker" to enable direct application in the classroom and to address the demand for active learning in PD [22]. These proven unplugged materials for the computer science classroom teach the basic ideas of AI and consider the need for communication and networking among teachers.

Table 3: Rough schedule for the second day

Introduction to Data Science and Orange (1h)
Decision Tree Learning, Inform. Gain, Confusion Matrix (2h)
k-Nearest Neighbors (0.5h)
Lunch break (1h)
Perceptron unplugged, Delta Learning, Implementation (2h)
Open discussion (time varies)

The final on-site day after completing the MOOC delves into some of the content beyond the MOOC, highlighting possible classroom implementations (see Table 3). Its structure is modular so that the content can be flexibly adapted to the needs of the respective learning group. On the one hand, certain curriculum-specific content (e.g. k-nearest neighbors, details on the delta learning rule of a perceptron, or applying machine learning from a data science perspective) that is only briefly touched on in the MOOC is explored in greater depth. On the other hand, various possibilities for classroom implementation are explored using tried and tested materials. For instance we employ a twine-clothespin-perceptron as an example to get started with neural networks. This is somewhat similar to the brain-in-a-bag activity [20] but adapted to facilitate delta-learning in a single neuron. For implementing hands-on data analysis with machine learning, we use Orange [4], a visual data analysis tool commonly used in the context of data analysis in K-12 [8]. Orange is very well suited for beginners, as due to the visual and data-flow oriented approach, no profound programming skills are required. At the same time, complex projects can be realized. With a short introduction to Orange, the participants can take their first steps in using the program with a straightforward example. A decision tree for a classification problem is then implemented, and the results are analyzed and discussed with regard to the quality of the resulting model using the confusion matrix (see [26]). Furthermore, the societal and ethical perspective of using AI models is discussed based upon concrete scenarios of unreliable, discriminatory, or faulty AI systems – simultaneously demonstrating approaches on how to integrate this topic in the classroom in the sense of the "pedagogical double-decker" once more.

This sequence (on-site day, MOOC, on-site day) will be offered approximately ten to twelve times between January 2023 and April 2024, as needed.

5 EVALUATION AND EXPERIENCES

As of this writing (December 2023), the PD program has been fully implemented in six cohorts with 146 participants (and one currently ongoing). About 94 % completed the offer. Of the remaining 6 %, four participants aborted during the MOOC. The other five were ill during the second on-site day of attendance, but still finished the course individually.

In order to assess teachers' prior experience in AI and to evaluate the PD, we used a *progress test* (cf. [31]) we developed previously, given the lack of standardized instruments for assessing

[2] https://open.sap.com/courses/ai1

AI competencies and knowledge. It consists of 15 questions in a closed-response format that covers most of the learning objectives intended for the entire PD offer. The 15 questions combine simple multiple-choice questions (with more than one valid answer) and drag-and-drop tasks to match answers accordingly. Areas such as the history of AI and the reasons for recent advancements in the field, characteristics of AI problems, or identifying applications that use AI are addressed. It also asks about the distinction between strong and weak AI as well as knowledge-based AI vs. machine learning. The latter is mapped in more detail in the test, as questions aim at different machine learning approaches, the handling of data, or algorithmic bias.

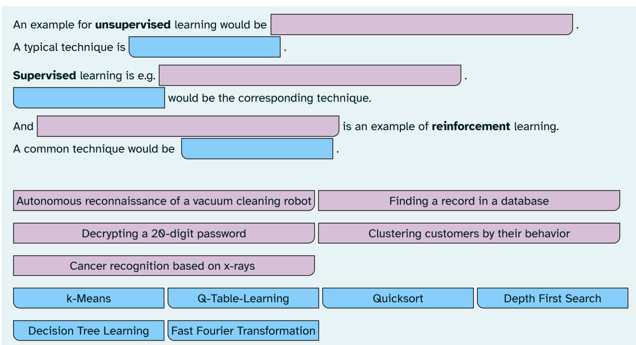

Figure 4: Exemplary question from the progress test: Match applications and techniques to the three types of machine learning

Teachers are asked to complete the test (online in about 20 minutes) before the first session and repeat it with identical questions at the end of the sequence (i.e., two months later). Participants do not receive feedback on their individual answers, but only the overall percentage result and can indicate “I don’t know” for each question to prevent guessing.

Figure 5: Pre-test before the course. Comparison of cohorts 1 and 2 (n=63), 3 (n=25), 4 (n=29), 5 (n=10), 6 (n=8), and 7 (n=9) for teachers that took part in the progress test

If we look at the teachers’ previous experiences, we see the expected heterogeneity (cf. fig. 5). However, we were surprised by the large proportion of participants who already achieved a very high score in the pre-test, in particular in cohort 1 and 2. We assume that many of the participants in the very first cohorts were particularly motivated teachers who had already familiarized themselves extensively with the topic – at this time, it was still more than a year before the first lessons on AI would take place. Anecdotal impressions from the sessions and conversations with teachers confirm this hypothesis. Areas where below-average prior knowledge was evident included knowledge-based approaches to AI, the history of AI, the data lifecycle, and how a perceptron works.

For the six cohorts that already finished the PD, the analysis of the results (cf. figure 6, only individuals for whom we were able to establish a match from pre-test to post-test) shows significantly better performance (t test, $p < 0.0001$).

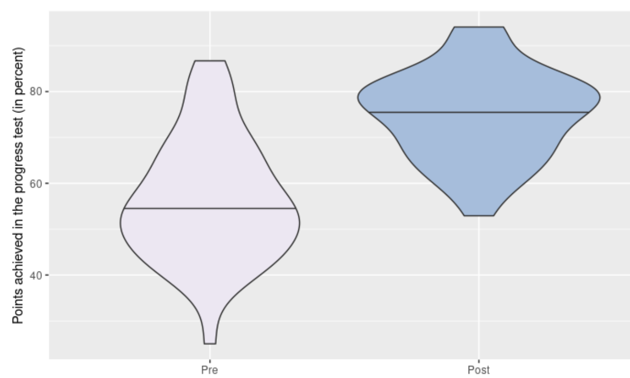

Figure 6: Pre-post comparison of cohorts 1 to 6, where matching was possible (n=42)

Regarding the teachers perception of the PD offer, on the one hand, we draw on numerous informal conversations during and after the sessions. On the other hand, one author conducted semi-structured interviews with three teachers, which were exploratory in nature. The interview contained questions about the self-assessment of the teachers’ professional and pedagogical competencies concerning AI. Besides, it addressed implementing the content learned in the PD in classroom.

In general, we received very positive feedback from teachers that confirms the success of the PD program. In the conversations, the teachers indicated that they feel well prepared for teaching AI after going through the PD, while having to look at some materials in detail again for the implementation in the classroom, as the following interview excerpt illustrates:

> "I think I’m very well prepared regarding the curriculum now, i.e., the new curriculum for the late-start variant. For the deepened-variant, I probably would have to make a few little things again. Especially the implementation in a programming language, whereby I think it is not part of the curriculum [in year 11]."[3]

[3]All quotes have been translated into English by the authors with minimal adjustments to improve comprehensibility.

In particular, the teachers appreciate that many of the materials can be used directly in their lessons and are convinced that the unplugged materials presented in the PD offer can be used profitably with students. The large number of requests where to get the unplugged games, which we use to introduce reinforcement and unsupervised learning on the first day, support our anecdotical impression from the conversations. The interviews also indicate this conclusion, as the following statement exemplifies:

> "I think these role-playing games are really good. And I have the feeling that the students, from what I have now tried out, also found it really great."

Using the unplugged neural network was not only very fun to the teachers. We also could observe how they developed their model of a neural network, especially the delta-learning rule. However, it became evident that explaining the game's rules clearly at the beginning is essential.

Furthermore, teachers highlighted the benefit of the advanced organizer. It helped them to get an overview of this broad topic and supported them in building their cognitive structures during the whole program. This is not surprising, as the literature has confirmed that an AO facilitates the entry into a new learning subject and supports long-term learning (see for example [33]). Having made this experience by themselves and being convinced of its benefit, teachers indicated to pass the AO to their students as well.

During the second on-site day, we observed that around one-third of the participants had quite some difficulties using the tool Orange. About half of this day revolves around understanding and implementing the k-nearest neighbors algorithm and decision-tree-learning with Orange. To our surprise, some teachers had problems using Orange, calling it 'unintuitive'. We can hardly understand this reproach. But such powerful "high ceilings" tools always need a specific training period. We suspect the problems could result from teachers' educational background combined with a general skepticism towards new technology tools.

The scalability of the PD offer is evident in the fact that we have already exported the format, with little modifications, to more rural areas of Bavaria and another German state, that is also about to introduce the topic into its K-12 CS curriculum. In order to address the different requirements due to the different curriculum of the teachers there, we kept the principal structure of the offer but changed some details in the content and structure. For example, we held the first on-site day as a video conference to keep long journeys for us and the participants to a minimum. We could easily adjust the modular design of the PD to get a well-designed offer for this group of educators.

6 CONCLUSION

In this paper, we have outlined the design of a PD offer on artificial intelligence for K-12 CS teachers and reported our experiences in the implementation. The need for the PD arose from the fact that AI takes up a large part of the mandatory CS curriculum for all students in year 11 (starting in the 23/24 school year). All over the world, we are confronted with CS being established as a mandatory subject or AI being introduced in CS curricula. Our approach can help design PD offers for (in-service) teachers in CS and in AI in particular, on a large scale while saving resources.

The main takeaways are summarized briefly as follows. We found that a blended learning format is ideally suited to ensure the scalability of a PD offer while addressing a large heterogeneity of participants. While developing the PD, we were confronted with various challenges, such as only a short period of time to design the offer, limited personnel resources, as well as a large number of teachers who were and are to be qualified. Furthermore, our target group has very heterogeneous degrees in CS education and prior knowledge. AI, in particular, has not been a part of any of their (formal) education. By using a modular structure combined with a blended learning format, we were able to meet these challenges. We have not only already educated close to 150 teachers with few personnel resources so far, but we also exported the PD offer to other regions and another federal state.

Our results indicate that the design of our PD, based upon principles for effective PD offers from literature (such as active learning or using classroom-ready materials), not only supported the effect of the in-service PD, but also led to satisfaction among the teachers. Our approach of the "pedagogical double-decker" guarantees that not only content knowledge is conveyed but that the teachers also experience pedagogical content knowledge. The numerous different approaches with many hands-on materials enabled active engagement of teachers during the PD and ensured direct implementation in the classroom.

Further questions to be answered in the context of the PD would be, in particular, the teachers' experiences when teaching AI for the first time in a compulsory curriculum. In this sense, longtime support for teachers would also be desirable, as the PD research calls for. Concrete questions to be asked are how well teachers felt prepared for the lessons regarding their content knowledge but also their ability for implementation in the classroom. Of course, looking at the student's perspective (emotional and cognitive) is also interesting and necessary. During the PD, we present many materials that still need to be evaluated in large-scale studies for their implementation in the classroom. The setup of compulsory teaching AI in year 11 would offer optimal conditions to investigate how teachers use the material and how they adapt it for their purposes. The results of future studies could be used not only to develop the materials and the PD further, but also to improve the teaching of AI.

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