(Authors' Draft)

Professional Development for Teachers in Artificial Intelligence and Data Literacy

Viktoriya Olari[1[0000-0002-5113-6624]], Till Zoppke[1[0000-0002-8921-8350]], Martin Reger[2[0000-0003-0828-926X]], Evgenia Samoilova[2[0000-0003-3858-901X]], Martin Kandlhofer[3[0000-0001-6410-2071]], Valentina Dagienė[4[0000-0002-3955-4751]], Ulrike Lucke[2[0000-0003-4049-8088]], and Ralf Romeike[1[0000-0002-2941-4288]]

[1] Freie Universität Berlin, Königin-Luise-Str. 24-26, 14195 Berlin, Germany
{viktoriya.olari,till.zoppke,ralf.romeike}@fu-berlin.de
[2] Universität Potsdam, An der Bahn 2, 14476 Potsdam-Golm, Germany
{mareger,evgenia.samoilova,ulrike.lucke}@uni-potsdam.de
[3] Österreichische Computer Gesellschaft, Wollzeile 1, 1010 Vienna, Austria
martin.kandlhofer@ocg.at
[4] Vilnius University, Universiteto 9, 01513 Vilnius, Lithuania
valentina.dagiene@mif.vu.lt

Abstract. Artificial Intelligence (AI) is gaining ground in school curricula worldwide, leading to an urgent need to train teachers in AI and data literacy. However, according to recent literature reviews, there is a lack of research-based professional development for teachers in these areas. In the following paper, we outline the steps we have taken to fill this gap by developing a 7-hour professional development program for teachers using the action research approach and evaluating it with 70 computer science teachers using a mixed methods approach. The results show that the program has increased teachers' perceived competence in introducing students to AI and improved their understanding of AI concepts. However, there is no clear evidence that a 7-hour program is sufficient for teachers to teach AI and data literacy related content in their classes.

Keywords: Data Literacy · Artificial Intelligence Literacy · Teacher Education · Action Research · Mixed Methods

1 Introduction

In response to the rapid development of artificial intelligence (AI) technologies and their ubiquity in children's lives, UNESCO member countries are taking steps to implement *AI Literacy and Data Literacy (AI&DL)* at various levels of K-12 education [1]. These are two distinct sets of skills. The former is a set of competencies that enables individuals to develop and critically evaluate AI technologies, to communicate and collaborate effectively with AI, and to use AI as a tool online, at home, and at work [2]. The latter intersects with the former, serves as its essential component [1], and is associated with the ability to critically collect, manage, evaluate, and apply data [3]. However, the key to the effective integration of AI&DL into school education is the effective preparation of teachers [4, 5]. Despite the growing number of academic publications on AI education [6], according to recent literature reviews [7–10], there is a lack of research on professional development programs for AI&DL.

Through our research, we take a step towards filling this gap. Based on the requirements for professional development programs for teachers as identified through (i) dialogue with European policymakers and (ii) a review of European education policies, we created a one-day professional development program for in-service computer science (CS) teachers, none of whom had prior knowledge of AI. The program is based on the Dagstuhl Triangle Model [11] and was evaluated with 70 CS teachers from Germany, Austria and Lithuania under the guidance of the following two research questions (RQ):

1. What is the effect of the designed program on CS teachers' perceived competencies to incorporate AI&DL into their teaching repertoire and on their understanding of AI&DL concepts?
2. To what extent are teachers able and willing to incorporate AI&DL content introduced in the program into their teaching, and what are the potential barriers?

In the following, we present the program structure, evaluation approach and instruments, and our findings. We begin by reviewing existing professional development programs for teachers on AI&DL and the policy frameworks that support teacher professional development on AI&DL in Section 2. In Section 3, we then outline the process we used to design and evaluate the program. In Section 4, we present details of the program format. The implementation of the program with 70 CS teachers is reported in Section 5 and finally, in Section 6, we discuss key findings.

2 Related work

In a recent systematic literature review, Sanusi et al. [7] found that there is a lack of teacher training programs that include AI for K-12, although we found some recent research. Jeon et al. [12] developed a teacher training for primary and secondary teachers using the ADDIE (analyze, design, develop, implement, evaluate) model and conducted a case study with 21 participants in South Korea. Their training concept included unplugged approaches for elementary schools and block-based programming combined with physical computing for secondary schools. More recently, Lee et al. [13] presented how a professional development program could be conducted in the form of an AI book club, where teachers spend a few hours a week independently reading selections from an AI book, reviewing AI activities, and then meeting online to discuss the materials. We also noted the development of a variety of courses on AI&DL for the general public (e.g., Elements of AI [14]) and for teachers specifically (e.g., the National Progression Award in Data Science for teachers in the United Kingdom [15]). However, we could not find any research describing the design choices, implementation, and effectiveness of these programs.

There are a number of educational guidelines and recommendations that recognize the need for professional development for in-service teachers. For example, a recent Organization for Economic Cooperation and Development (OECD) working paper stated that continuing professional learning is vital for teachers to broaden and deepen their knowledge, keep up with new research, tools and practices and respond to their students' changing needs [16]. Regarding education for technological developments, the European Union (EU) recently published the European Digital Competence Framework *DigComp 2.2* [17]. The document includes a list of more than 80 examples of knowledge, skills and attitudes related to citizens interacting with AI systems. Data literacy is one of the framework's five competence areas. For teachers specifically, the EU has published the *Framework for the Digital Competence of Educators (DigCompEdu)*, which focuses specifically on digital competences for teachers [18]. The most recent version of this document is from 2017, and does not mention data literacy or AI literacy. However, in the *Digital Education Action Plan (2021-2027)*, the EU takes note of the rapid changes in digital communication and use. The document contains 14 actions, divided into two main priorities. Specifically, Action Six focuses on "Ethical guidelines on the use of AI and data in teaching and learning for educators" and Action Eight deals with "Updating the European Digital Competence Framework to include AI and data-related skills" [19]. More documents on global education policy on AI can be found in the multidisciplinary repository of the OECD *AI Policy Observatory* [20]. For European countries, a similar visualization of national AI initiatives is provided by the Council of Europe [21].

3 Methodology

To develop a professional development program, we followed the action research approach [22]. Action research is characterized by its iterative nature, involving multiple cycles of planning, action, observation, feedback, and reflection. As suggested by Dittrich et al. [23], the process consisted of three phases:

Phase 1 - Understanding Practice: We conducted research on the availability and common practices of professional development for CS teachers. We then examined 38 education policies from Germany, Austria and Lithuania, as well as specific EU-wide policies, to understand the requirements for introducing AI&DL into teacher education. In addition, we conducted a cycle of four workshops with 87 policy makers from public authorities, research and education and collected recommendations on program formats and methods, possible ways to integrate AI&DL into professional development and best practice examples [24, 25]. We also conducted a review of existing pedagogical frameworks for AI and data literacy in teacher education [26] and reviewed competency areas, pedagogical approaches, contexts and formats for introducing AI literacy in schools [27].

Phase 2 - Deliberate Improvements: We designed a one-day professional development program on AI&DL for secondary school CS teachers. We focused on in-service CS teachers because this audience is naturally exposed to the teaching of technology-related topics in schools. Prior to implementation, we conducted a pilot session with CS teachers to test whether the underlying concepts were appropriate for the participants' prior knowledge and experience.

Phase 3 - Implement and Observe Improvements: We implemented the developed program in Germany, Austria, and Lithuania. To gain an understanding of the impact of the sessions, we used a mixed methods approach following Creswell's concurrent nested design [28]. This design allowed us to enrich and clarify our quantitative findings with qualitative data.

Quantitative data collected through *pre- and post-evaluation surveys* and *pre- and post-knowledge tests* enabled us to evaluate the effectiveness of the program. The survey items measured perceived competence in introducing AI&DL into the classroom. Sample items and the measurement scale are presented in Figure 1. The surveys also included questions about participants' attitudes toward AI&DL in the school context and post-program feedback about the suitability of the selected topics and materials used in the professional development for CS school education. The pre- and post-knowledge test contained 14 multiple-choice knowledge questions about the understanding of the AI concepts introduced in the session. No question went above the understanding level (the lower level) of Anderson's taxonomy [29]. We did not test higher levels because the post-questionnaire time was very short and we could only get a quick snapshot of concept understanding. An example of an AI concept question was: "Classical AI systems are particularly suitable when: (A) the number of possible results grows exponentially with increasing input parameters; (B) expert knowledge is available; (C) the problem space can be described unambiguously; (D) the application requires speech or image recognition; (E) don't know". Choosing all options correctly (B, C, not A, not B) earned the participant 1 point. Choosing three correct options and one incorrect option (A, B, C, and not B) earned the participant 0.75 points. If option (E) was selected, the participant received 0 points. The Wilcoxon signed-rank test was used to analyze the quantitative data. This test compares two related samples, specifically the pre- and post-measures, taken from the same individuals.

Qualitative data were collected through *semi-structured personal interviews* conducted immediately after the sessions. The interviews provided insights into the participants' perspectives on professional development provided in the course and their thoughts on integrating AI&DL into their teaching practice. The interviews were transcribed and analyzed using summarizing content analysis [30] and focused content analysis [31]. Intercoder reliability could not be tested because only one main coder was involved. To reduce coding bias, the coder corresponded with other researchers to code questions. Saturation was assessed by examining whether new data ceased to generate new themes or categories.

Several limitations should be noted when interpreting the results. First, data were collected from a limited number of participants, which affects the generalizability of the results. Second, we were not able to evaluate the quality of the survey instruments prior to their use in the field. However, we made the survey instruments and interview guidelines available to researchers to better understand our procedure and results [32].

4 Designing the professional development program

The design of the professional development program was guided by insights from the policy analysis in Phase 1, literature reviews in the field of AI education, and the Dagstuhl Triangle Model [11]. The main insights that we considered from Phase 1 were: to provide teachers with ready-to-use teaching materials and tools; to design a professional development with a duration of 7 hours; to combine unplugged teaching approaches with tools to actually develop small AI systems; to provide a self-assessment test for teachers to determine their existing knowledge. We built the program around two components: (1) content knowledge - the subject matter to be learned and taught, and (2) pedagogical knowledge - the process and methods of teaching and learning. Table 1 outlines the structure of the program and the learning objectives for each phase.

In terms of content knowledge, following the Dagstuhl Triangle model, we focused (i) on fundamental paradigms of machine learning, rule-based AI, and the data lifecycle (technological perspective), (ii) ethical use of data in AI systems (socio-cultural perspective), (iii) building systems based on machine learning, and conducting data analysis (application perspective), as these are recurring and overarching themes in international policy and educational frameworks [17, 33]. We also introduced teachers to national curricula and guidelines on AI&DL as informed by policy work, so that teachers could refer to them when incorporating new topics into their teaching.

For the pedagogical knowledge, we based the program on the *didactic biplane* [34], which is commonly used for CS professional development for teachers. According to this method, the facilitator conducts the session in the same way as a teacher would in the classroom. The teachers take on the role of the students and work with the materials as they would use them in their classes. This method allows both pedagogical and content knowledge to be addressed simultaneously, thereby increasing teachers' understanding of the topic and enabling them to learn how to use the materials. We selected research-based, unplugged and computer-based educational materials that have been successfully tested with students and are based on fundamental ideas of machine learning, rule-based AI, and the data lifecycle [35–37]. All materials are published and open source, and include suggestions for classroom use, including recommended timing and lesson structure [38]. The majority of the activities targeted the Understanding Level of Anderson's Taxonomy. The data analysis project targeted higher levels (apply, analyze, evaluate).

Table 1. Outline of the one-day, 7-hour professional development program.

Activity	**Learning Objectives**	**Description**	**Materials**
AI Bingo	Recognize AI in real-world settings and activate prior knowledge	Participants guess whether a given computer system is an AI application	Images
Round of introductions	Participants and the facilitator know each other	Each person introduces him- / herself	-
Intro to AI and AI&DL	Become familiar with AI terminology; be aware of international guidelines on AI\&DL and national curricula including AI&DL.	The facilitator presents an overview of AI, outlining the role of data in this process and international frameworks and guidelines for AI\&DL; another local facilitator presents national curricula relevant to AI\&DL.	Slides
Beat the robot	Explain the idea of classical AI and contrast classical and reinforcement learning approach.	Define a classical AI that plays hexapawn; train an agent that plays hexapawn	W KI-B3.2
Customer prototypes	Experience and explain the unsupervised learning paradigm	Identify cluster centers by replaying the vector quantization algorithm	W KI-B3.5
Biting and non-biting monkeys	Experience and explain the supervised learning paradigm	Classify monkeys with a decision tree and evaluate the result in a confusion matrix	W KI-B4.1
		Lunch break	
Intro data literacy and data lifecycle	Know the data analysis workflow; understand basic statistical concepts	The facilitator presents an overview about data science	Slides
First steps in Orange3	Explore Orange3 and implement an explorative data analysis workflow	Classify monkeys in biting and non-biting ones	W KI-B4.2; PC
Data analysis project	Create, train and test predictive models with the data mining tool Orange3	Analyze a sample data set with real-world data	W KI B4.3; PC
Review and discussion	Visualize ways to integrate activities in their own classroom	The facilitator summarizes the workshop; participants share their feedback	Slides

5 Results of the program implementation and evaluation

We conducted three professional development sessions in Germany, Lithuania, and Austria from June 2022 to January 2023. The recruitment of CS teachers for the sessions was supported by local partners. All participants were CS teachers at the secondary level in grades five to 12 (Lithuania) or five to 13 (Germany, Austria). A significant number of teachers had never taught AI (29 out of 70). 59 participants were fully qualified teachers, six were pre-service teachers, and five were in their post-university traineeship (*Referendariat* in German). The average age of the participants was 43-45 years. The gender distribution varied across the countries. In Germany and Austria there was a low proportion of women (22% and 16% respectively). In Lithuania the proportion of women was high (57%). One participant in Germany and Austria identified as non-binary or diverse. Table 2 provides information on the response rates for the pre- and post-evaluation surveys and the pre- and post-knowledge tests for each program. We conducted post-program interviews with CS teachers who volunteered to participate: six in Germany, eight in Lithuania, and six in Austria.

Table 2. Response rates for pre- and post-survey and pre- and post-knowledge test.

Training	**No. of Participants**		**Pre-Response**		**Post-Response**		**Pre- and Post-Response**	
	Survey	Test	Survey	Test	Survey	Test	Survey	Test
Germany, 2022-06	24	24	23 (96%)	19 (80%)	21 (88%)	20 (83%)	20 (83%)	16 (67%)
Lithuania, 2022-12	21	21	21 (100%)	19 (90%)	17 (81%)	18 (86%)	16 (76%)	14 (67%)
Austria, 2023-01	25	25	19 (76%)	21 (84%)	15 (60%)	11 (44%)	14 (56%)	11 (44%)

5.1 Teachers' perceived competencies and understanding

Overall, the program contributed to an increase in participants' perceived competence, particularly in how to incorporate AI content into their teaching (see Figure 1). While the extent of the increase and its statistical significance varied, the overall trend was positive. On average, post-program DL scores improved significantly (at the 1% level) in Germany and increased slightly in Lithuania and Austria, while AI scores increased significantly (at the 1% level) across all sessions. There was also an observable improvement in the understanding of AI concepts in all three countries (see Figure 2). Improvements in DL varied, with significant gains on objective tests observed only in Austria (5% level). In the post-survey, participants rated the suitability of the topics and practical examples for CS education on a 6-point scale, with 1 being 'not at all suitable' and 6 being 'very well suitable'. The feedback showed that the topics of knowledge-based AI and machine learning were highly valued in Germany and Lithuania, with around 80-90% of respondents rating the suitability as high/very high. In Austria, the topic of machine learning was also rated the highest by 67% of respondents. The data lifecycle topic and the Orange3 example were rated less favorably in all countries.

According to the qualitative results from all three countries, the program mainly provided basic knowledge. According to some participants, Orange3 would be difficult to understand (Germany, Lithuania), and while other topics (e.g., AI) were considered easy, it was acknowledged that these complex and expansive areas would in fact require further commitment from teachers to deepen their knowledge. The length of the program was considered to be good for the content being taught (all countries). However, given the depth of knowledge required, additional sessions or input was suggested. In both Germany and Austria it was noted that there was a lack of connection between the AI and DL parts of the program. In Germany and Lithuania, however, the structure of the program was praised. The desire to include more topics was expressed in all countries.

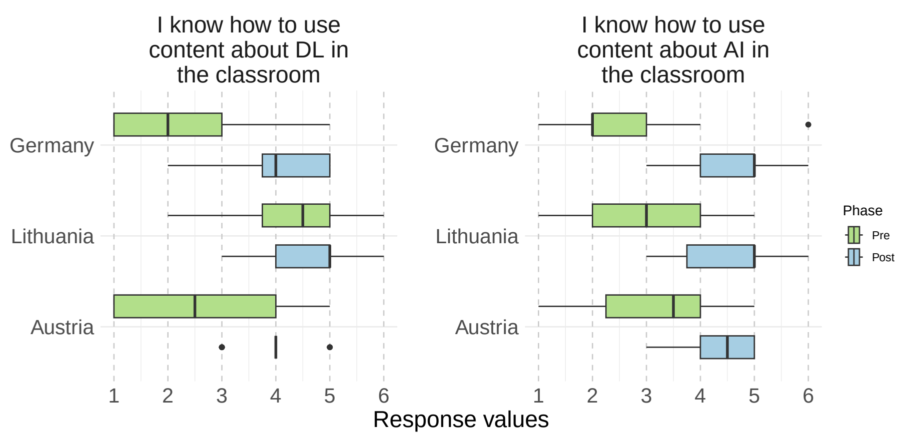

Fig. 1. Response distributions for the pre- and post- results of the survey on teachers' perceived competences to introduce AI&DL-related content in the classroom. For each item, teachers were asked, "How much do you agree with the following statements?" and were given a scale from 1 (not at all) to 6 (definitely).

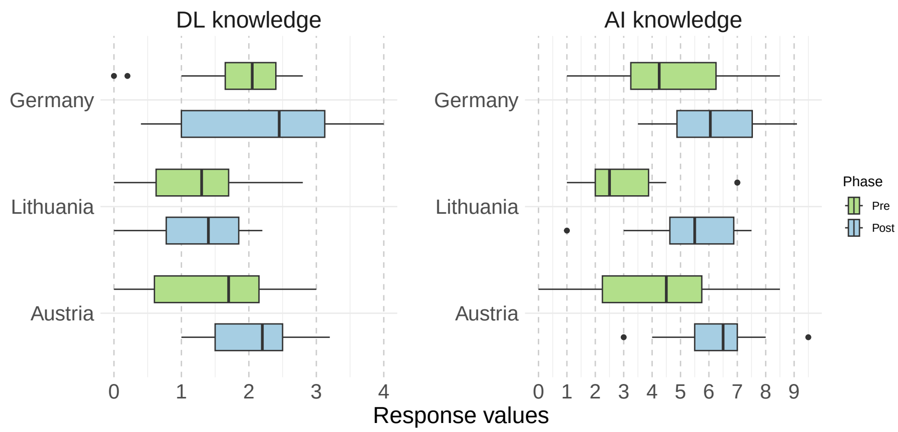

Fig. 2. Response distributions for the pre- and post-results of the knowledge test. The test consisted of four knowledge questions for the DL dimension and ten for the AI dimension. For example, in Germany, the average number of correct answers for the AI dimension was 4.1 before participating in the program and 6 after participating in the program.

5.2 Perceived ability, willingness and barriers

In the post-survey, participants were asked to rate their agreement with the following statements: 'I am willing to invest time and effort to incorporate DL/AI into my teaching,' and 'After the training, I have gathered enough competences to teach the learned content in class.' They responded on a scale from 1 (strongly disagree) to 6 (strongly agree). The results for these two items suggest that, on average, participants from all three program sessions generally expressed a strong willingness to invest time and effort in incorporating both AI and DL into their teaching, with a higher willingness observed for AI compared to DL. In Germany and Austria, the results indicate a moderate level of agreement that participants have acquired sufficient competencies to teach the learned content in the classroom. In Lithuania, the results show a trend towards agreement that participants have acquired sufficient competences.

In the interviews, materials related to the exercises that could later be used by teachers in the classroom were highly valued (all countries). Respondents from all countries indicated that unplugged materials could be used to integrate topics into CS education. However, there were respondents who were unsure whether immediate integration was possible, arguing that only basic knowledge was provided during the session (Lithuania, Austria).In all countries, it is noted that teachers would need to engage more with the themes and content of the program in order to teach it effectively.

Regarding the barriers, in some interviews in Germany and Austria it is stated that no or no major (institutional) barriers are expected for the integration of AI&DL in CS school education. On the other hand, time constraints, such as high teacher workload, are frequently mentioned in all countries. Another barrier is the settling-in period when introducing new topics into subjects/teaching (Austria). In Lithuania, the fast pace of AI&DL topics is seen as a challenge. ChatGPT is seen as having significant potential for change and as a challenge (Lithuania, Austria).

6 Discussion

In our research, we designed, implemented, and evaluated a 7-hour professional development program on AI and data literacy for in-service CS teachers to enable them to incorporate AI&DL topics into their teaching.

Overall, the results indicate a positive effect of the designed program. We found that a one-day professional development program in AI is sufficient to increase subjectively perceived and objectively demonstrated competence in AI, with variable improvements in data literacy. This finding may seem trivial, as one could argue that teachers would naturally know more after the program than before. However, it is questionable whether competencies for teaching AI can be effectively achieved in 7 hours, since a new topic like AI requires the acquisition of specialized technical skills and practice. The fact that teachers actually learned something and felt more competent afterwards, rather than realizing what they did not know and feeling insecure, is interesting. However,according to the quantitative data, there is no clear evidence that a one-day program is sufficient to actually integrate AI&DL into the classroom. The qualitative results showed a similar trend: teachers were able to gain a basic knowledge of how to teach AI in their CS classrooms using the program's content and materials, but at the same time, there was a desire for more than basic knowledge to do so effectively. However, as the policy work in Phase 1 indicated, providing more time for CS teachers to participate in longer programs is a challenge.

In terms of teachers' ability and willingness to incorporate the AI, machine learning content and materials introduced in the program, the results were mixed. The knowledge-based AI and machine learning topics, introduced through unplugged materials, were highly valued and perceived as appropriate for CS classrooms. The data lifecycle topic introduced through computer-based materials was perceived as less relevant and appropriate for the school context. We do not have comparable results from previous research using the same materials. However, consistent with the teacher ratings, previous research has reported positive results for the unplugged approach for both students and teachers [39]. We are surprised that data literacy received mixed reviews and was less popular among CS teachers. We initially assumed that CS teachers would associate data literacy experiences with teaching data modeling topics that are part of a regular CS school curriculum. Perhaps more time to work with Orange3 could improve the rating. Providing additional scaffolding should also be considered, as previous research has shown that understanding and preparing the data is generally a time-consuming and tedious task [40].

The results indicated that major barriers for CS teachers were time constraints (current workload, settling-in period, fast pace of technology) and lack of knowledge. However, with a few exceptions [13, 15], we could not find any research-based, long-term professional development programs for teachers on the topic of AI&DL. Future research is needed to design and evaluate such programs and their effects. Longitudinal studies of the integration of AI&DL into teacher education and the evaluation of the long-term effects of such interventions are, in our view, a promising direction for research.

7 Conclusion

This paper presents results from the development of a professional development program for CS teachers on AI. Overall, the results showed that teachers' perceived competence in introducing AI into CS education increased, as did their understanding of AI concepts. While improvements in data literacy were also positive, the statistical significance varied. In future work, following the action research approach, we will incorporate the results of the evaluation into the design of further professional development programs for CS teachers. In future research cycles, we also intend to apply the findings to elementary and STEAM teachers, as well as to the preparation of pre-service teachers during their undergraduate studies.

8 Acknowledgements

We would like to thank Erasmus+ Programme of the European Union for financial support as a part of the project "TrainDL – Teacher training for Data Literacy & Computer Science competences".

References

1. UNESCO: K-12 AI curricula: a mapping of government-endorsed AI curricula. No. ED-2022/FLI-ICT/K-12, Paris (2022)
2. Long, D., Magerko, B.: What is ai literacy? competencies and design considerations. p. 1–16. CHI '20, Association for Computing Machinery, New York, NY, USA (4 2020). https://doi.org/10.1145/3313831.3376727
3. Ridsdale, C., Rothwell, J., Smit, M., Bliemel, M., Irvine, D., Kelley, D., Matwin, S., Wuetherick, B., Ali-Hassan, H.: Strategies and best practices for data literacy education knowledge synthesis report (2015)
4. Miao, F., Holmes, W.: International Forum on AI and Education: Ensuring AI as a Common Good to Transform Education, 7-8 December 2021; synthesis report - UNESCO Digital Library. No. ED-2022/WS/14, France
5. Ayanwale, M.A., Sanusi, I.T., Adelana, O.P., Aruleba, K.D., Oyelere, S.S.: Teachers' readiness and intention to teach artificial intelligence in schools. Computers and Education: Artificial Intelligence **3**, 100099 (2022)

6. Tenório, K., Olari, V., Chikobava, M., Romeike, R.: Artificial intelligence literacy research field: A bibliometric analysis from 1989 to 2021. In: Proceedings of the 54th ACM Technical Symposium on Computer Science Education V. 1. p. 1083–1089. ACM, Toronto ON Canada (Mar 2023). https://doi.org/10.1145/3545945.3569874
7. Sanusi, I.T., Oyelere, S.S., Vartiainen, H., Suhonen, J., Tukiainen, M.: A systematic review of teaching and learning machine learning in k-12 education. Education and Information Technologies **28**(5), 5967–5997 (May 2023). https://doi.org/10.1007/s10639-022-11416-7
8. Marques, L.S., Gresse Von Wangenheim, C., Hauck, J.C.R.: Teaching machine learning in school: A systematic mapping of the state of the art. Informatics in Education **19**(2), 283–321 (Jun 2020). https://doi.org/10.15388/infedu.2020.14
9. Zhou, X., Van Brummelen, J., Lin, P.: Designing ai learning experiences for k-12: Emerging works, future opportunities and a design framework (Sep 2020). https://doi.org/10.48550/arXiv.2009.10228
10. Olari, V., Cvejoski, K., Eide, : Introduction to machine learning with robots and playful learning. Proceedings of the AAAI Conference on Artificial Intelligence **35**(17), 15630–15639 (5AD)
11. Diethelm, I.: Digital education and informatics – you can't have one without the other. In: Proceedings of the 17th Workshop in Primary and Secondary Computing Education. WiPSCE '22, Association for Computing Machinery, New York, NY, USA (2022). https://doi.org/10.1145/3556787.3556790
12. Jeon, I.S., Jun, S.J., Song, K.S.: Teacher Training Program and Analysis of Teacher's Demands to Strengthen Artificial Intelligence Education. Journal of The Korean Association of Information Education **24**(4), 279–289 (Aug 2020)
13. Lee, I., Zhang, H., Moore, K., Zhou, X., Perret, B., Cheng, Y., Zheng, R., Pu, G.: Ai book club: An innovative professional development model for ai education. In: Proceedings of the 53rd ACM Technical Symposium on Computer Science Education. p. 202–208. ACM, Providence RI USA (Feb 2022)
14. The University of Helsinki, M.: A free online introduction to artificial intelligence for non-experts - elementsofai.com. https://www.elementsofai.com, [Accessed 29-09-2023]
15. Farrell, K., Watts, J.: Data Science: Educators' Guide to the National Progression Award. The University of Edinburgh (2020)
16. Boeskens, L., Nusche, D., Yurita, M.: Policies to support teachers' continuing professional learning (235) (2020). https://doi.org/10.1787/247b7c4d-en
17. Vuorikari, R., Kluzer, S., Punie, Y.: Digcomp 2.2: The digital competence framework for citizens - with new examples of knowledge, skills and attitudes. Scientific analysis or review, Luxembourg (Luxembourg) (2022). https://doi.org/10.2760/115376
18. Redecker, C., Punie, Y.: European framework for the digital competence of educators: Digcompedu. Scientific analysis or review, policy assessment, technical guidance, Luxembourg (Luxembourg) (2017). https://doi.org/10.2760/159770
19. European Commission: Digital education action plan (2021-2027) (2021)
20. OECD.AI: Ec/oecd (2021), database of national ai policies (2023), https://oecd.ai/en/dashboards/overview
21. Council of Europe: Ai initiatives (2023), https://www.coe.int/en/web/artificial-intelligence/national-initiatives
22. C. Hong, Salika Lawrence: Action research in teacher education: Classroom inquiry, reflection, and data-driven decision making. Journal of Inquiry and Action in Education (2011)

23. Dittrich, Y., Rönkkö, K., Eriksson, J., Hansson, C., Lindeberg, O.: Cooperative method development: Combining qualitative empirical research with method, technique and process improvement. Empirical Software Engineering **13**(3), 231–260 (Jun 2008). https://doi.org/10.1007/s10664-007-9057-1
24. The TrainDL project: Traindl interactive policy monitor, https://traindl-policymonitor.ocg.at/
25. Austrian Computer Society OCG: Teacher training for data literacy computer science competences, https://train-dl.eu/fileadmin/GI/Projekte/Train-DL/TrainDL_Deliverable_1_1.pdf
26. Olari, V., Tenório, K., Romeike, R.: Introducing artificial intelligence literacy in schools: A review of competence areas, pedagogical approaches, contexts and formats. In: Keane, T., Lewin, C., Brinda, T., Bottino, R. (eds.) Towards a Collaborative Society Through Creative Learning. pp. 221–232. Springer Nature Switzerland, Cham (2023)
27. Olari, V., Romeike, R.: Addressing ai and data literacy in teacher education: A review of existing educational frameworks. In: Proceedings of the 16th Workshop in Primary and Secondary Computing Education. WiPSCE '21, Association for Computing Machinery, New York, NY, USA (2021). https://doi.org/10.1145/3481312.3481351
28. Creswell, J.W.: Designing and conducting mixed methods research. SAGE, Thousand Oaks, California, third edition edn. (2018)
29. Anderson, L.W. (ed.): A taxonomy for learning, teaching, and assessing. A revision of Bloom's taxonomy of educational objectives - abridged edition. Rev. ed. Longman, New York, NY u.a. (2001)
30. Mayring, P.: Qualitative Inhaltsanalyse: Grundlagen und Techniken. Pädagogik, Beltz, Weinheim and Basel, 11., aktual. und überarb. aufl. edn. (2010)
31. Kuckartz, U., Rädiker, S.: Fokussierte Interviewanalyse mit MAXQDA: Schritt für Schritt. Springer eBook Collection, Springer VS, Wiesbaden (2020)
32. Reger, M., Samoilova, E., Lucke, U., Tsymboulova, A.: (2023), https://train-dl.eu/fileadmin/GI/Projekte/Train-DL/14-12-23_D4_4_final.pdf
33. Michaeli, T., Romeike, R., Seegerer, S.: What students can learn about artificial intelligence – recommendations for k-12 computing education. In: Keane, T., Lewin, C., Brinda, T., Bottino, R. (eds.) Towards a Collaborative Society Through Creative Learning. pp. 196–208. Springer Nature Switzerland, Cham (2023)
34. Wahl, D.: Lernumgebungen erfolgreich gestalten: vom trägen Wissen zum kompetenten Handeln; mit Methodensammlung. Julius Klinkhardt (2013)
35. Lindner, A., Seegerer, S., Romeike, R.: Unplugged activities in the context of AI. In: Pozdniakov, S.N., Dagiene, V. (eds.) Informatics in Schools. New Ideas in School Informatics - 12th International Conference on Informatics in Schools: Situation, Evolution, and Perspectives, ISSEP 2019, Larnaca, Cyprus, November 18-20, 2019, Proceedings. Lecture Notes in Computer Science, vol. 11913, pp. 123–135. Springer (2019)
36. Michaeli, T., Seegerer, S., Kerber, L., Romeike, R.: Data, trees, and forests-decision tree learning in k-12 education. In: The Third Teaching Machine Learning and Artificial Intelligence Workshop. pp. 37–41. PMLR (2023)
37. Grillenberger, A., Romeike, R.: About classes and trees: Introducing secondary school students to aspects of data mining. In: Pozdniakov, S.N., Dagiene, V. (eds.) Informatics in Schools. New Ideas in School Informatics - 12th International Conference on Informatics in Schools: Situation, Evolution, and Perspectives, ISSEP 2019, Larnaca, Cyprus, November 18-20, 2019, Proceedings. Lecture Notes in Computer Science, vol. 11913, pp. 147–158. Springer (2019)

38. Seegerer, S., Michaeli, T., Romeike, R.: https://computingeducation.de, https://computingeducation.de/proj-it2school/
39. Bell, T., Vahrenhold, J.: CS Unplugged - How Is It Used, and Does It Work?, pp. 497–521. Springer International Publishing, Cham (2018)
40. Zha, D., Bhat, Z.P., Lai, K.H., Yang, F., Jiang, Z., Zhong, S., Hu, X.: Data-centric Artificial Intelligence: A Survey (Jun 2023)