Wirtschaftsinformatik 2024 Proceedings | Wirtschaftsinformatik

2024

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Maximilian Förster
Ulm University, Germany, maximilian.foerster@uni-ulm.de

Kirsten Pitz
Ulm University, Germany, kirsten.pitz@uni-ulm.de

Andrea Wrabel
Ulm University, Germany, andrea.wrabel@uni-ulm.de

Mathias Klier
Ulm University, Germany, mathias.klier@uni-ulm.de

Steffen Zimmermann
Ulm University, Germany, steffen.zimmermann@uni-ulm.de

Building AI Literacy with Experiential Learning – Insights from a Field Experiment in K-12 Education

Research Paper

Maximilian Förster, Kirsten Pitz, Andrea Wrabel, Mathias Klier, and Steffen Zimmermann

Ulm University, Institute of Business Analytics, Ulm, Germany
{maximilian.foerster, kirsten.pitz, andrea.wrabel, mathias.klier, steffen.zimmermann}
@uni-ulm.de

Abstract. Integrating AI literacy into K-12 education has become a global strategic initiative. Despite an increase in innovative approaches based on hands-on-experiences, there is a lack of theoretical and empirical insights on their effectiveness. To address this, we examine the effect of experiential learning on building AI literacy in K-12 students. We build on experiential learning theory (ELT) to develop hypotheses and conduct a randomized field experiment with 1,346 German high school students. Our results indicate that an experiential learning-based AI lesson (1) can enhance AI literacy in terms of higher AI knowledge, higher AI readiness, and lower AI anxiety, (2) might be more effective than a classical AI lesson in building AI literacy in students with low AI affinity, but slightly increases AI anxiety, and (3) is positively evaluated by teachers.

Keywords: AI Literacy, Experiential Learning, Field Experiment, K-12

1 Introduction

Rapid advancements in Artificial Intelligence (AI) led to its omnipresence in the workplace and everyday life (Makridakis, 2017). However, society faces the challenge of inappropriate understanding and use, as well as negative perceptions of AI due to low AI literacy (Rigley et al., 2024; Zhang and Dafoe, 2019). This can have severe negative consequences for individuals, businesses, and society as a whole (Milad et al., 2022), such as privacy violations, spread of misinformation, and social and economic inequality (Yampolskiy, 2018). Establishing a comprehensive understanding, calibrated attitude, and appropriate use of AI has become a global demand (Long and Magerko, 2020). To educate the general public from an early age and enable the effective interaction with AI in daily life, practitioners and researchers strongly advocate for integrating AI education into K-12 curricula (Chiu et al., 2022; Steinbauer et al., 2021).

The distinct characteristics of AI – high learning capacity, autonomy, and inscrutability (Berente et al., 2021) – pose major challenges to building AI literacy. In response, the number of research articles developing innovative learning approaches has increased considerably since 2019 (Sanusi et al., 2023). Many approaches aim at building AI literacy through hands-on experience and interaction with real AI (Druga et al., 2022). This experiential learning approach seems particularly promising, as complex AI concepts can be difficult to comprehend and may even remain inscrutable despite understanding their theoretical foundations (Jiang et al., 2022; Baird and Maruping 2021). Experiential learning facilitates to build AI literacy through transformation of experience with the actual functioning of AI. To the best of our knowledge, the effectiveness of experiential learning to build AI literacy has not yet been investigated. Indeed, research on building AI literacy in K-12 education has been criticized for a lack of theoretical rigor and empirical evidence (Chiu et al., 2022; Sanusi et al., 2023) and neglecting teachers' perspectives (Steinbauer et al., 2021). With our study, we aim to address these shortcomings and state the following research question:

How does experiential learning affect the building of AI literacy in K-12 students?

To answer this question, we draw on experiential learning theory (ELT) (Kolb, 1984) to develop hypotheses about the effect of experiential learning on building AI literacy in K-12 students and conduct a randomized field experiment with 1,346 students from 47 German high schools. The students are divided into three groups: one that did not receive any lesson, one that received a classical AI lesson, and one that received the same AI lesson with the only difference that contents were conveyed through experiential learning. We find that a single experiential learning-based AI lesson can already have a positive effect in terms of reducing AI anxiety and increasing AI readiness. Our study further provides first indications that an experiential learning approach is more effective than a classical approach in building AI literacy in students with low AI affinity and is positively evaluated by teachers, but slightly increases AI anxiety compared to the classical approach. These findings contribute to the literature on AI education and ELT and help educators to effectively build AI literacy in K-12 students.

2 Related Literature

Students frequently interact with AI in various applications, such as chatbots and recommender systems, in their daily lives (Su et al., 2023b). Thus, it is not surprising that integrating AI education into K-12 curricula has become a global strategic initiative (Steinbauer et al., 2021) to help students understand the technologies they interact with (Touretzky et al., 2019) and prepare them for future jobs where AI will play a role (Heintz, 2021). For example, the AI for K-12 initiative (AI4K12) – and similar initiatives all over the world – aim at developing curricular guidelines to build AI literacy in K-12, to educate the public about AI (Steinbauer et al., 2021; Kandlhofer et al., 2021).

Integrating AI into K-12 education has attracted considerable interest among researchers (Sanusi et al., 2023). Respective research is motivated by two challenges associated with building AI literacy. First, teaching the theoretical foundations of AI is not sufficient to establish AI literacy. Although AI literacy was initially defined as the ability to understand the basic techniques and concepts of AI (Burgsteiner et al., 2016; Kandlhofer et al., 2016), this definition has been extended in recent years to a set of competencies, including meta-competencies, to ensure a critical and meaningful use of AI (Dai et al., 2020; Ng et al., 2021). Specifically, AI literacy includes competencies for working effectively with AI and thus requires an understanding of how AI works in real-word applications. The actual functioning of AI depends on what has been learned implicitly based on the underlying data. As a consequence, AI may appear inscrutable to humans, even if they know its theoretical foundations (Baird and Maruping, 2021; Jiang et al., 2022). To illustrate, knowing the representation of a neural network in the form of neurons and layers does not necessarily translate into an understanding of the behavior of a neural network in an application. Thus, approaches are needed to teach AI's actual functioning. Second, based on research on AI curriculum development, building AI literacy should not only include AI knowledge, but also meta-competencies such as a calibrated attitude towards AI (Chai et al., 2020; Lin et al., 2021).

Research addresses these challenges by developing novel approaches to build AI literacy. These approaches can be divided into formal and informal education. While informal education is characterized by an unstructured, unintentional, and spontaneous learning process, formal education is more structured, intentional, and systematic as well as typically conducted in a classroom setting (Steinbauer et al., 2021). Current research efforts focus on formal approaches with the aim of integrating AI education into school curricula (Sanusi et al., 2023). Many proposed approaches involve experiential learning, where students gain hands-on experience and interact with real AI systems to learn about their functioning and usage (Evangelista et al., 2018; Sanusi et al., 2023). To this end, researchers often use customized AI tools (Su et al., 2023a; Yau et al., 2023). Kandlhofer et al. (2019), for instance, propose an approach in which high school students build and program a household service robot to learn about and experience AI. Similarly, Lin et al. (2020) introduce Zhorai, a conversational agent for students to explore AI's functioning. Druga et al. (2022) suggest building AI literacy through training an AI model, changing its parameters, and observing the corresponding AI outcomes. However, evaluation of these approaches is scarce. In this vein, Lin et al. (2020) employed pre- and post-assessments to determine whether students demonstrated increased AI understanding after completing their course. However, they did not compare their approach to a benchmark or classical approaches and evaluated their approach only on a sample of 14 participants. Accordingly, the effectiveness of experiential learning in the context of AI education has not yet been thoroughly investigated (Chiu et al., 2022; Sanusi et al., 2023). With our study, we aim to address this gap by investigating the effectiveness of experiential learning to build AI literacy – in comparison to a classical learning approach – from students' and teachers' perspectives.

3 Theoretical Background and Hypotheses Development

Previous studies have shown that students have more AI knowledge after taking a course about AI (Su et al., 2023a). However, due to the distinct characteristics of AI, building AI knowledge among K-12 students has been a major challenge in the past, especially for non-technical learners, as complex AI concepts can be difficult to understand (Chiu et al., 2022). As outlined in Section 2, many studies that aim at developing innovative approaches to build AI literacy include hands-on experiences and can be characterized as experiential learning approaches (Lee and Kwon, 2024; Yue et al., 2022). Experiential learning is one of the most widely used approaches in educational research and practice, has been applied in various disciplines including Information Systems (IS), and has been shown to have positive effects on the learning process and learning outcomes (Hsu et al., 2022; Jewer and Evermann, 2015). The underlying theory, experiential learning theory (ELT)[1] (Kolb, 1984), considers learning as a process of building knowledge through the transformation of experience. The learning process includes a four-stage cycle of concrete experience, reflective observation, abstract conceptualization, and active experimentation (Kolb, 1984). Research has shown that the structure of the ELT process can help students to think step-by-step, so that they can construct concepts more logically and actively reflect on what they have learned (Hsu et al., 2022). Moreover, the different activities involved in the ELT learning process encourage students to acquire and transform concrete experiences, abstract concepts and models into meaningful information (Young et al., 2008). Thus, experiential learning may be particularly beneficial for building AI literacy, as it supports learners to understand the abstract and difficult concepts of AI through hands-on experience when interacting with AI technology. Consequently, and in line with previous research, we expect an experiential learning-based AI lesson to increase students' AI literacy.

As outlined in Section 2, AI literacy encompasses both AI knowledge and meta-competencies like a calibrated attitude towards AI. AI knowledge comprises the understanding of basic techniques and concepts of AI and its actual functioning in real-world applications. Meta-competencies such as AI readiness and AI anxiety are critical in shaping perceptions and attitudes towards AI (Chai et al., 2020; Lin et al., 2021). Despite prevalent positive attitudes towards AI (Bitkom, 2023), concerns about its future development persist (Johnson and Verdicchio, 2017). AI anxiety, often caused by uncertainty (Li and Huang, 2020), can be mitigated by providing more information, thus reducing uncertainty and increasing familiarity with the technology. This approach can boost students' confidence in their abilities, enhancing their readiness to use AI. Increased AI readiness can significantly influence their learning and future use of AI, bridging the gap between technology and daily life (Tomlinson et al., 2003).

Overall, we expect that the experiential learning-based AI lesson will contribute to students' AI literacy in three ways: increasing AI knowledge, boosting AI readiness, and reducing AI anxiety. Thus, we state our first hypothesis:

***H1:** Students who receive an experiential learning-based AI lesson exhibit higher levels of AI literacy, in terms of (a) increased AI knowledge, (b) increased AI readiness and (c) decreased AI anxiety, than students who do not receive an AI lesson.*

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[1] An alternative theoretical foundation is technology-mediated learning (TML) (Alavi et al., 2001). TML uses information technology (i.e., tools, digital platforms) to mediate interactions between learners, teachers, and learning materials. However, learners may feel overwhelmed by complex online systems, fail to make full use of available learning resources, and miss opportunities to interact with trainers (Lo et al., 2017). As integrating ELT with technological tools may foster more critical thinking, practical application, and personal engagement, we thus choose ELT as our theoretical foundation.

Building AI literacy can be challenging due to its rather complex and intricate nature, which requires a strong mathematical background and computational thinking skills (Wong et al., 2020). Unlike classical teaching of AI concepts, which is characterized by a teacher-centered instruction and often does not actively engage students, experiential learning encourages active exploration and a more gradual learning curve (Kolb, 1984). Existing research in education in various disciplines (e.g., science, engineering) has consistently shown that the adoption of experiential learning can have a positive impact on student engagement by actively involving students in the learning process through hands-on activities (Li et al., 2019). In this sense, Jewer and Evermann (2015) found an increase in student engagement among students who participated in an experiential learning-based IS course. Hence, we also expect an experiential learning-based AI lesson to increase student engagement and state the second hypothesis as follows:

H2: *Students who receive an experiential learning-based AI lesson exhibit higher student engagement, than students who receive a classical AI lesson.*

As outlined above, building AI literacy requires an active and participatory approach to ensure deep understanding and application of concepts. Previous studies in other domains indicate that an experiential learning-based approach can outperform classical learning approaches in terms of learning outcomes (Chiu et al., 2023), as students can better grasp core concepts through hands-on activities (Lee and Kwon, 2024). Experiential learning could encourage students to think more reflectively about AI, which also could promote a deeper understanding of AI's actual functioning (Chan, 2012). Therefore, we expect that experiential learning will outperform classical learning approaches when it comes to AI literacy. Accordingly, we hypothesize:

H3: *Students who receive an experiential learning-based AI lesson exhibit higher levels of AI literacy, in terms of (a) increased AI knowledge, (b) increased AI readiness, and (c) decreased AI anxiety, than students who receive a classical AI lesson.*

4 Research Methodology and Study Design

To investigate the effect of an experiential learning-based AI lesson on building AI literacy, we conduct a randomized field experiment with German high school students. A randomized field experiment allows us to establish causal relationships by controlling for extraneous variables, ensuring observed effects are attributed to the learning approach (Harrison and List, 2004). Conducted in a real-world setting, it also provides valuable practical insights. In our experiment, we provide students with an AI lesson based on either an experiential learning or a classical learning approach. In addition, we include a control group that does not receive an AI lesson to gain insights into whether a short intervention in the form of a 90-minute lesson can improve students' AI literacy. The classical and experiential learning-based AI lessons have the same content, learning objectives, and materials. The only difference between the lessons is the learning approach. This allows us to isolate the effect of experiential learning and make a controlled comparison between the two learning approaches. The AI lessons are carried out by university teaching assistants, while teachers attend as passive observers.

The introductory phase of both AI lessons focuses on a lecture-style presentation of how supervised learning and neural networks work. Thereby, image recognition is used as a concrete example to illustrate these concepts. In the second phase, both AI lessons include a deep dive into the topic of supervised learning in the form of exercises. The focus here is on gaining insights into the effects of balanced, unbalanced, and inaccurate training data on AI's functioning in order to build a nuanced understanding of the challenges and intricacies of training AI. This is where the difference between the two learning approaches comes into play: While the students in the classical AI lesson solve the exercises in pairs based on the knowledge that was provided in the introductory phase, in the experiential AI lesson, students are provided with an AI tool (see Figure 1) to solve the (same) exercises. The AI tool allows students to interact directly with a real AI system that is trained for image recognition based on the MobileNetV2 architecture. Hereby, students go through Kolb's Learning Cycle of concrete experience, reflective observation, abstract conceptualization and active experimentation (Kolb, 1984). Using the AI tool, students are presented with an image containing three objects. By selecting sections of the image for the AI to recognize, students can discover where the AI is reliable, but also where it reaches its limits. Hereby, students can observe the AI's actual functioning. Students can further select the (amount and labels of) training data and experience how the AI's functioning changes. This allows for active experimentation with data and labels, encouraging reflection on the implications of training an AI system for image recognition.

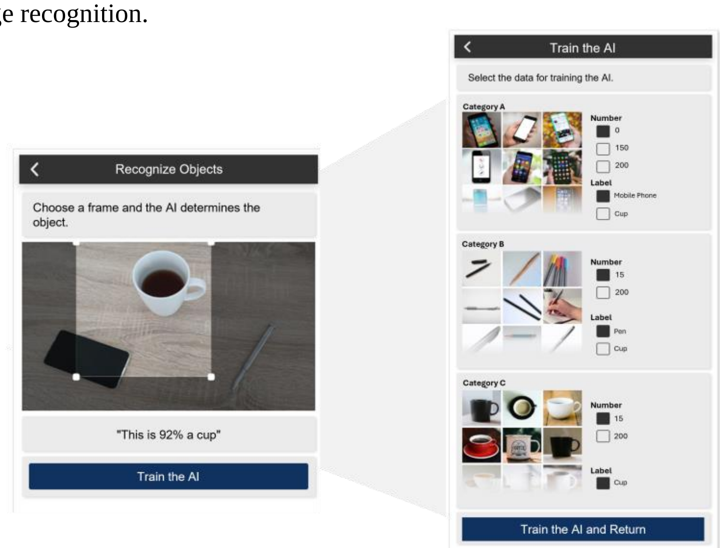

Figure 1. Experiential Learning-based AI Tool (https://test.xaidemo.de/education/)

In the third phase of both AI lessons, the solutions for the exercises are discussed in class. This is followed by a final transfer in which potentials and limitations of AI are discussed based on what was learned in the deep dive. Approximately one week after the AI lesson, the students complete a questionnaire that serves as a means for our data collection. Students in the control group also complete a questionnaire without previously attending our AI lesson. To test our hypotheses on the effects of an experiential learning-based AI lesson on AI literacy, we include several main and control variables (see Table 1).[2] The main variables, including the knowledge test questions, were developed in accordance with constructs and items from existing studies.

Table 1. Main and Control Variables for the Student Questionnaire

Main Variables
AI Knowledge Test (Seven single choice questions inspired by Rodríguez-García et al. (2021) and Melsión et al. (2021))
Self-Assessed AI Understanding[1] (Three items adapted from Jewer and Evermann (2015))
AI Readiness[1] (Five items adapted from Chai et al. (2020) and Dai et al. (2020))
AI Anxiety[1] (Five items adapted from Wang and Wang (2022))
Student Engagement[1,2] (Three items adapted from Jewer and Evermann (2015))
Control Variables
Gender, Math Grade, Computer Science Grade, Self-Assessed Math Performance compared to Peers, Computer Science Affinity[1], AI Affinity[1], Math Affinity[1], Region, School Type, Class Grade, Technical Issues, Questionnaire Type (Paper-based, Mobile, Desktop)
Additional Control Variables for AI Lesson[2]
Self-Assessed Learning[1] (Three items adapted from Jewer and Evermann (2015)), Assessment of Teaching Assistant[1] (Three items adapted from Mang et al. (2021)), Teaching Assistant of Lesson, Number of Students in Lesson, Time between Lesson and Questionnaire (in Days)

[1] Items based on 7-point Likert scales (1 = strongly disagree to 7 = strongly agree)

[2] As these variables refer to the AI Lesson, they are not part of the questionnaire for the control group

After the AI lessons were conducted, we send a questionnaire to the teachers, who passively observed the lessons, to get a more comprehensive understanding of their perceptions of the AI lessons. We ask them to evaluate the lessons in terms of perceived difficulty, student enthusiasm, and student participation (one item for each) based on 7-point Likert scales, add questions about grade and course appropriateness and ask if they would recommend the AI lesson. We also include open-ended questions to ask about their overall feedback and the perceived impact of the lesson on their students.

Prior to the main experiment, we conducted a pilot study in two classes at a collaborating school to improve the comprehensibility of our materials and to minimize potential problems or misunderstandings (Reynolds and Diamantopoulos, 1998). We then revised the AI lessons and questionnaires. The main experiment was conducted in June and July 2022 with 11th and 12th grade students from 93 classes in 47 schools in the administrative districts of Stuttgart and Tuebingen in Baden-Wuerttemberg (Germany). Randomization for treatment was at school level and all classes in the same school received the same treatment. Overall, 14 university teaching assistants delivered the lessons, each of whom delivered both classical and experiential AI lessons.

[2] An outline of the student and the teacher questionnaire as well as extended summary statistics including controls is provided via https://github.com/ISresearch77/Build_AILit_ExpLearn.

5 Analysis and Results

A total of 1,346 11th and 12th grade high school students participated in our field experiment. Before analyzing our data, we removed participants who did not finish the questionnaire (89 observations) or were in classes with significant technical problems, such as poor Internet connectivity, which prevented the AI lessons from being properly conducted (242 observations). The final dataset includes 1,015 participants, with 417 participants in the control group, 381 participants who received the classical AI lesson, and 217 participants who received the experiential learning-based AI lesson. Before examining this data, we calculate Cronbach's alpha for multi-item variables to ensure internal consistency of our scales (Cortina, 1993). As Cronbach's alpha is above the recommended value of 0.7 (Hair et al., 2011) for all multi-item variables, we keep all proposed items and aggregate the items for the respective variables.

5.1 Effect of an Experiential Learning-based AI Lesson on AI Literacy

To get a first impression of the effect of an experiential learning-based AI lesson on AI literacy compared to the control group, Table 2 Panel A presents the summary statistics for our main variables. The last column shows the difference in means between both groups and whether this difference is statistically significant. Statistical significance is assessed based on Wilcoxon rank-sum tests or t-tests. In line with our expectations, we observe a significantly higher AI literacy in terms of higher AI knowledge, higher self-assessed AI understanding, higher AI readiness, and lower AI anxiety for students who received an experiential learning-based AI lesson. To test H1, we turn to a multivariate regression to investigate the effect of an experiential learning-based AI lesson on AI literacy in terms of a) AI knowledge (H1a), b) AI readiness (H1b) and c) AI anxiety (H1c). Thus, we estimate the following ordinary least squares (OLS) models:

$$AI_{Knowledge/Readiness/Anxiety} = \alpha + \beta\ ExpLearn_{Control} + \delta\ Controls + \epsilon \qquad (1)$$

where $AI_{Knowledge}$, $AI_{Readiness}$ or $AI_{Anxiety}$ serve as dependent variables. $AI_{Knowledge}$ is operationalized via the number of correct answers to the AI knowledge test (AI_{Test}) and via self-assessed AI understanding ($AI_{SelfUnd}$). The independent variable of interest is $ExpLearn_{Control}$, which is a dummy variable being one for the group receiving an experiential learning-based AI lesson and zero for the control group. We further include relevant control variables ($Controls$, see Table 1). ϵ represents the remaining error term, and we use robust standard errors clustered by school. Results are shown in Table 2 Panel B. As expected, we observe a positive and significant coefficient for the experiential learning-based AI lesson on the correct answers to the AI knowledge test ($\beta = 1.527, p < 0.01$) and self-assessed AI understanding ($\beta = 1.135, p < 0.01$). Furthermore, we observe a positive and significant coefficient for AI readiness ($\beta = 0.143, p < 0.05$) and a negative and significant coefficient for AI anxiety ($\beta = -0.267, p < 0.01$). Thus, an experiential learning-based AI lesson leads to higher AI knowledge – which is rather obvious –, but further affects students' attitude towards AI resulting in higher AI readiness and lower AI anxiety supporting H1.

Table 2. Results for the Effect of an Experiential Learning-based AI Lesson on AI Literacy

Panel A. Summary Statistics

	Control Group (n=417)				Experiential Learning-based AI Lesson (n=217)				Diff. in Means
	Mean	SD	Min	Max	Mean	SD	Min	Max	
AI_{Test}	4.29	1.67	0	7	5.64	1.26	1	7	1.35***
$AI_{SelfUnd}$	4.10	1.29	1	7	5.18	0.92	2	7	1.08***
$AI_{Readiness}$	4.46	0.85	1.4	7	4.64	0.81	1.8	6.8	0.18***
$AI_{Anxiety}$	4.43	0.99	1.8	6.8	4.13	1.00	1.4	7	-0.30***

Panel B. OLS Results (*compared to the Control Group)*

	Effect	SE
$AI_{Lesson} \rightarrow AI_{Test}$	1.527***	0.138
$AI_{Lesson} \rightarrow AI_{SelfUnd}$	1.135***	0.080
$AI_{Lesson} \rightarrow AI_{Readiness}$	0.143**	0.061
$AI_{Lesson} \rightarrow AI_{Anxiety}$	-0.267***	0.073

Notes: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. *Statistical significance is based on a Wilcoxon rank-sum test ($AI_{SelfUnd}$, $AI_{Readiness}$, $AI_{Anxiety}$) and a t-test (AI_{Test}) in Panel A. Panel B shows the results of an OLS regression including control variables with robust standard errors (SE) clustered by school.*

5.2 Effects of Experiential Learning vs. Classical Learning on Student Engagement and AI Literacy

We are also interested in the effect of the chosen learning approach in terms of an experiential learning-based AI lesson compared to a classical AI lesson. Again, to get a first impression of the differences between the two learning approaches, Table 3 Panel A presents the summary statistics of the main variables, now additionally including student engagement. Statistical significance is again assessed using Wilcoxon rank-sum tests and t-tests. Based on these univariate tests, we do not observe significant differences in the main variables and turn to the multivariate regression analyses. To test whether experiential learning has an effect on student engagement, we estimate the following OLS model:

$$StudEng = \alpha + \beta\ ExpLearn_{Classic} + \delta\ Controls + \epsilon \qquad (2)$$

where student engagement ($StudEng$) is the dependent variable. In this and the following analyses, $ExpLearn_{Classic}$ is our independent variable and represents a dummy variable being one for receiving the experiential learning-based AI lesson and zero for receiving the classical AI lesson. We further include the relevant (extended) set of control variables ($Controls$, see Table 1). ϵ represents the remaining error term and we use robust standard errors clustered by school. The results are shown in Table 3 Panel B.

Surprisingly, we do not observe a significant effect of experiential learning on student engagement and thus reject H2.

Table 3. Results for the Effect of an Experiential Learning-based AI Lesson vs. a Classical AI Lesson on Student Engagement and AI Literacy

Panel A. Summary Statistics

	Classical AI Lesson (n=381)				Experiential Learning-based AI Lesson (n=217)				Diff. in Means
	Mean	SD	Min	Max	Mean	SD	Min	Max	
$StudEng$	5.12	1.10	1	7	5.04	1.08	1	7	-0.08
AI_{Test}	5.48	1.60	0	7	5.64	1.26	1	7	0.16
$AI_{SelfUnd}$	5.28	0.97	1	7	5.18	0.92	2	7	-0.10
$AI_{Readiness}$	4.67	0.85	2	7	4.64	0.81	1.8	6.8	-0.03
$AI_{Anxiety}$	4.16	1.04	1	7	4.13	1.00	1.4	7	-0.03

Panel B. OLS Results

	All Students:		*Students with low AI Affinity:*	
	Effect	SE	Effect	SE
$ExpLearn \rightarrow StudEng$	0.126	0.079	0.191	0.202
$ExpLearn \rightarrow AI_{Test}$	0.248	0.196	0.975**	0.453
$ExpLearn \rightarrow AI_{SelfUnd}$	0.015	0.037	-0.171	0.319
$ExpLearn \rightarrow AI_{Readiness}$	-0.030	0.063	-0.329	0.297
$ExpLearn \rightarrow AI_{Anxiety}$	0.127**	0.061	-0.384	0.281

Notes: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. *Statistical significance is based on a Wilcoxon rank-sum test ($StudEng, AI_{SelfUnd}$, $AI_{Readiness}$, $AI_{Anxiety}$) and a t-test (AI_{Test}) in Panel A. Panel B shows the results of an OLS regression including control variables with robust standard errors (SE) clustered by school.*

Next, to examine the effect of experiential learning compared to classical learning on AI literacy as hypothesized in H3, we estimate an OLS model similar to the one in Eq. 1, but with $ExpLearn_{Classic}$ as independent variable instead of $ExpLearn_{Control}$. Further, we include the same set of control variables as for the analysis of student engagement and add student engagement to this set. As presented in Table 3 Panel B, we do not observe a significant effect of experiential learning on the correct answers to the AI knowledge test, self-assessed AI understanding and AI readiness. For AI anxiety, however, we observe a significant and positive coefficient ($\beta = 0.127, p < 0.05$). In other words, the experiential learning-based AI lesson is similarly effective as the classical AI lesson in building AI literacy, but slightly increases AI anxiety and we do not find support for H3. However, for investigating students with low AI affinity

($AI_{Affinity} < 4$)[3], we do not observe a significant effect on AI anxiety, but instead a positive and significant coefficient ($\beta = 0.975, p < 0.05$) on the correct answers to the AI knowledge test (Table 3 Panel B) indicating a potential benefit of the experiential learning-based AI lesson for this group of students.

5.3 Teachers' Perspectives on AI Lessons

To gain insights into the teachers' perspectives on our AI lessons, we examine the responses from the teacher questionnaires, with 6 teachers from the classical AI lesson and 10 from the experiential learning-based AI lesson[4]. Overall, the teachers do not perceive the AI lesson as too difficult (*means: classical = 1.3; experiential = 1.4*) and highly rate student enthusiasm (*means: classical = 5.7, experiential = 5.4*) and participation *(means: classical = 6.3, experiential = 5.7*). 9 out of 10 teachers would recommend the experiential learning-based AI lesson, while the recommendation rate for the classical AI lesson is 3 out of 6. Regarding the open-ended responses about the impact of the AI lesson on their students, teachers report that the lesson "*provided a nice insight into the topic*", led to a "*better understanding of the topic*", and that the students' "*interest was aroused*". Teachers of the experiential learning-based AI lesson more often mention a high level of interest and enthusiasm. The responses to the open-ended questions further provide aspects to consider in the future: Several teachers recommend incorporating the AI lessons earlier in grades 7-9, one even stating that AI topics should be taught "*in grade 7 at the latest*". Besides, they advocate for integrating AI into advanced courses, including additional topics, such as "*neural networks*", "*mathematical aspects*", or the "*application of AI in advertising*".

6 Conclusions, Implications, and Future Research

This study examines the impact of experiential learning on building AI literacy in K-12 students. Analyzing data from a randomized field experiment, we present the following key findings that contribute to theory and practice: First, we find that already a single experiential learning-based AI lesson can have a positive effect in terms of reducing students' AI anxiety and increasing their AI readiness. These findings contribute to the literature on AI education and suggest that experiential learning helps to adjust students' attitudes towards AI. Previous research highlights the importance of these meta-competencies, as AI anxiety can negatively affect learning motivation and academic performance (Wang et al., 2022; Zhang and Aslan, 2021), while AI readiness is crucial for its appropriate use in the future (Dai et al., 2020; Tang et al., 2021). Second, our results indicate that an experiential learning approach is more effective than a classical approach in building AI literacy in students with low AI affinity, significantly

3 The value of 4 equals "Neutral" on the 7-point Likert scale. 106 students had a low AI affinity (60 in the classical AI lesson, 46 in the experiential learning-based AI lesson).

4 Please note that we only consider teachers whose students received an AI lesson. Further, some teachers handled multiple classes, and some were not present for the entire lesson, leading to potential non-participation.

increasing their AI knowledge compared to the classical AI lesson. As low AI affinity among students might reduce their motivation and ability to learn about the complex fundamentals of AI, experiential learning may be particularly attractive for these students by allowing them to build AI literacy through direct hands-on experience. The attractiveness of the experiential learning-based AI lesson was further supported by the positive perceptions of the teachers who accompanied the AI lessons. Third, contrary to expectations, an experiential learning-based AI lesson did not outperform a classical AI lesson in fostering student engagement and building AI literacy across the full sample of 11th and 12th grade high school students, which contrasts ELT theory. This counterintuitive finding could be explained by the fact that students from higher grade levels already provide the skills needed to understand the complex and abstract concepts of AI, even if they have no opportunity to experience its real functioning.

With this study, we contribute to ELT and AI education research by being the first to extract the effectiveness of an experiential learning approach in building AI literacy compared to a classical approach. Our findings further extend the ELT by providing first indications that the effectiveness of experiential learning might be affected by the affinity towards the topic in terms of being particularly beneficial for learners with a low affinity. Given the strong need for innovative and curriculum-dependent approaches to build AI literacy (Lee and Kwon, 2024; Ng et al., 2023), educators can build on our findings to develop and promote experiential learning-based approaches to build AI literacy in K-12 students.

Although our study provides interesting insights, it is not without limitations. These limitations can serve as a starting point for future research. First, the lessons were delivered by 14 university teaching assistants rather than regular teachers. Although this was a feasible way to reduce the burden on the participating schools and to better control for the effects of different persons teaching, the long-term goal is to provide regular teachers with the necessary materials to integrate the lesson into their regular curriculum. This could make the setting even more realistic and rule out effects due to students' different behavior when a new person delivers the lesson. Furthermore, although we included the teachers' perspective by providing them with a brief questionnaire, future studies could gain more in-depth insights by extending the teacher questionnaire to include additional aspects, such as their ability to teach AI or a more detailed assessment of the materials. Another limitation of this study is that it only investigates short-term effects, as students' AI literacy was measured only once, after a short period of approximately one week. Therefore, future studies should investigate potential long-term effects to gain further insights. Finally, as our findings provide surprising indications that an experiential learning-based AI lesson might be beneficial in building AI literacy in students with low AI affinity, but not for the full sample of students, a more detailed investigation of the effects of experiential learning across different groups is needed. In this sense, future research could provide insights on how to effectively build AI literacy among different groups. Related to this, future studies could further investigate the effectiveness of an experiential learning-based AI lesson for younger students, other school types, or within the general public. This is in line with the teachers' suggestion to offer the AI lesson to younger students.

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