

Integrating data literacy into teacher education: Fostering reflection and critical thinking regarding AI

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The increasing prevalence of data-driven technologies, including artificial intelligence (AI), underscores the need to develop data literacy skills and the ability to critically reflect on these technologies. This is especially important in teacher education, as educators play a crucial role in fostering such competencies in future generations. However, the reflective discussion is underrepresented compared to the demonstration of the performance and learners find it challenging to connect theoretical concepts to their lives. A seminar concept for prospective math teachers was developed that explicitly aimed to stimulate reflections on mathematical foundations of AI and the implications for society and the students' own life. The material was tested twice. In the second iteration of the study, modifications were made by including concrete examples from the students' lifeworld. An analysis of the contextual references in the students' discussions shows that in the second round, indeed, more and more diverse context-related answers were given.

MOTIVATION

Data-driven technologies, including artificial intelligence (AI), have become ubiquitous in our daily lives – whether through the use of Google, navigation apps, streaming platforms, social media, or digital assistants in our homes. Increasingly, AI-powered systems are also being deployed in areas where decisions about individuals are made, such as in healthcare, applicant pre-selection, criminal justice, and counterterrorism. The application of AI in such contexts requires critical ethical consideration. Moreover, growing concerns are being raised about how the opacity and complexity of these technologies can result in systemic racial and gender biases (Sweeney, 2013), as well as lead to unfair decision-making processes (Barocas & Selbst, 2016).

It is therefore of great importance that citizens actively participate in essential political and societal discourses on these issues and are empowered to shape their professional and private lives in a responsible, self-reflective, and constructive manner. Such maturity requires a deep understanding and a realistic assessment regarding the opportunities and risks associated with these technologies (Vartiainen et al., 2021). To equip future generations with these competencies, the relevant knowledge must already be developed in teacher education (Casal-Otero et al., 2023).

This gives rise to the question of how to design a learning opportunity for prospective teachers that enables them to impart essential competencies related to AI technologies and to educate their future students to become informed and responsible citizens. One approach to develop such material is the implementation of a design-based research study (Prediger et al., 2015). Across multiple iterations, teaching and learning material is developed toward a specific objective, while the associated professionalization processes are systematically investigated to gain insights into typical learning trajectories and challenges. The findings from the studies are subsequently incorporated into the further refinement of the material.

THEORETICAL BACKGROUND AND RESEARCH QUESTIONS

As previously outlined, teachers should empower learners to independently form their own judgments in all areas of life, based on their personal thoughts and perspectives, to develop a stance and act accordingly in a self-determined manner. Mathematics also plays a role in this: According to Skovsmose (1998), social phenomena are structured by mathematics and ultimately constituted by it. Jablonka (2003) refers in this context to “mathematical literacy” which is required to critically examine aspects of life by means of mathematical knowledge and knowledge about mathematics.

For this reason, fostering reflective knowledge in mathematics education is of central importance. Skovsmose (1998) distinguishes four types of reflective knowledge: *mathematics-oriented* and *model-oriented* reflection assess whether calculations have been conducted correctly, whether an

algorithm functions properly, and whether the output of a modelling process is reliable. *Context-oriented* and *lifeworld-oriented* reflection go beyond abstract mathematics and modelling, asking: What is the actual purpose of the modelling? What are the political and societal implications of applying mathematics to this situation? What do the result and the calculation mean for me? (Skovsmose, 1998). For the attainment of mathematical literacy, reflection that is oriented toward real-world contexts and everyday life is of particular importance (Lengnink, 2006).

Accordingly, there is a need for learning environments at all levels of education that integrate knowledge about AI into mathematics instruction while explicitly promoting reflective knowledge. Ideally, strong connections to students' everyday life should be made so that the knowledge can be concretely applied in daily contexts (Höper & Schulte, 2024).

Several initiatives have already developed learning environments for different grade levels. For instance, Lindner et al. (2019) describe unplugged activities in the context of AI from a computer science perspective. A presentation of the activities can be found on the website www.aiunplugged.org, while a detailed theoretical foundation of the creation of the material is presented in Lindner (2025). Another example is the project <https://www.prodabi.de/en/> which provides lesson plans and material focused on data science. However, these resources primarily address technical and theoretical aspects as well as algorithmic implementation; explicit attention to critical reflection and ethical discussion is largely lacking.

As a first step within a design-based research study (Prediger et al., 2015), Büscher and Lengnink (in press) developed a seminar concept on AI in mathematics education that – beyond conveying fundamental mathematical concepts – deliberately prompts reflection. The teaching material is described in Büscher and Lengnink (in press). Insights into the learners' reflection processes are to be incorporated into the further development of the seminar concept.

To date, empirical research on reflection processes remains limited. Some studies have been conducted in the field of statistical literacy (Lengnink & Eckhardt, 2020; Büscher & Prediger, 2019). However, in the context of data science and AI, learners' reflective engagement with the subject matter is considerably less prominent than the demonstration of conceptual understanding (Bilstrup et al., 2022; Sanusi et al., 2023).

Büscher and Lengnink (in press) developed an analytical tool for examining learners' reflection processes at least for the seminar concept on AI in mathematics education which is described in the same article. One finding of the analysis presented there is that the students tend to establish relatively few connections to context in their reflections (Büscher & Lengnink, in press). For the further implementation of the seminar, the material has now been revised to encourage more context-related reflections. In the present contribution, we focus on one specific aspect, namely whether – and to what extent – the teaching and learning material elicit context-related responses. More precisely, the research question is:

To what extent do learners' reflections demonstrate context relevance? And how does this differ between the two design experiment cycles?

SEMINAR CONCEPT

Büscher and Lengnink (in press) developed a seminar concept for prospective mathematics teachers specifically designed to provoke reflection on the ethical and moral implications of AI models. The material incorporates content from www.aiunplugged.org on decision trees and is enriched with reflection tasks. It was implemented during one seminar session (90 minutes) as a first iteration of the design-based research study (see Büscher & Lengnink, in press). The analysis of the reflection processes from the first iteration indicates that the learners established only few links to the real-world context, and given that fostering responsible citizenship requires a tangible connection to learners' everyday lives (Höper & Schulte, 2024), the material was expanded for a second iteration to include two new components. First, participants were asked to identify instances of AI in their daily lives at the beginning of the seminar. Second, an excursion unit on reinforcement learning and its application in TikTok's recommendation algorithm was added. In addition, some of the reflection tasks were slightly rephrased or consolidated. The modified material was tested during a seminar and covered two sessions (180

minutes). The following section shortly presents the two versions of the teaching material, focusing on the elements relevant to the focus of this article.

Introduction (only in version 2): Image material from www.kiki-labor.fau.de/en/station01/ is presented, together with the question of which devices and everyday applications involve AI systems.

Phase 1 (in both version 1 and 2): Material from www.aiunplugged.org is used to explain the concept behind decision trees. Monkeys are to be classified as either biting or non-biting. Training data are provided, based on which a decision tree is to be constructed (Figure 1, A and B).

Phase 2 (only in version 2): New data are presented (Figure 1, D), and participants are asked to respond to reflection tasks 2.1 and 2.2 (Table 2).

Phase 3 (in both version 1 and 2): A monkey with previously unknown features (Figure 1, C) is presented, and reflection tasks 1.1–1.5 (version 1) and 2.3–2.5 (version 2), respectively, are assigned (Table 2).

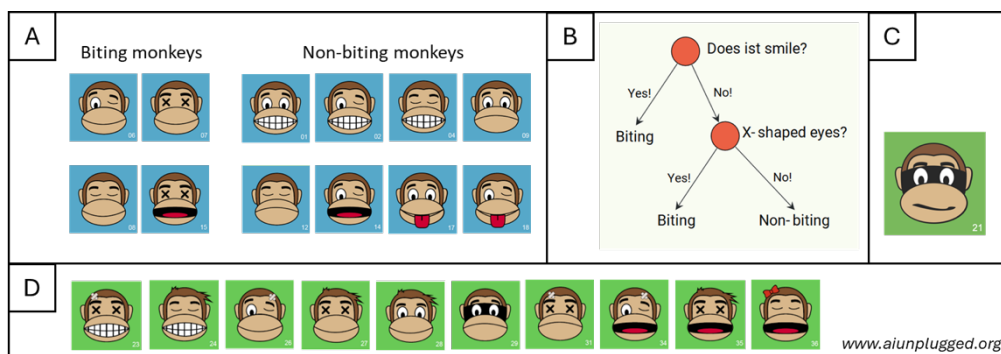


Figure 1. Training data (A), a possible decision tree (B) and a new monkey (C), new monkeys with partially new features (D) (www.aiunplugged.org)

Excursion (only in version 2): A unit on reinforcement learning and its application on TikTok is introduced. For this, the game “Beat the Crocodile” from www.aiunplugged.org is analysed, and the method of reinforcement learning is discussed. Subsequently, the application of this method on TikTok is explained, and learners are asked to consider the implications of personalised content for users, whether TikTok can influence opinions, and how to counteract such influences.

Phase 4 (in both version 1 and 2): Three real-world situations are presented in which algorithmic decision-making is already employed (Table 1). Reflection tasks 1.6–1.13 (version 1) and 2.6–2.12 (version 2), respectively, conclude the unit (Table 2).

Table 1. Real-world situations in which AI-driven decisions are made

S1	A court uses an algorithmic decision-making system to assess the likelihood of recidivism among offenders and to assign them to risk categories.
S2	A company uses an algorithmic decision-making system to pre-select job applicants.
S3	The Federal Employment Agency uses an algorithmic decision-making system to predict how quickly a job-seeking individual can be placed in new employment.

Table 2. Reflection tasks in the two versions of the seminar concept

Version 1		Version 2	
1.1	For what reason might the monkey not be classifiable?	2.1	Are false negative or false positive decisions more severe, and why?
1.2	How could such a situation be prevented?	2.2	What are the consequences if an incorrect decision results
1.3	What is the significance of an incorrect decision emerging because of the classification of a monkey?		

1.4	Do you consider it justifiable to employ algorithmic decision-making systems in the classification of monkeys? Why or why not?		from the classification of a monkey?
1.5	Would you also use such systems in other contexts? If so, in which ones and why?	2.3	Why might the use of the above decision tree be considered problematic in this case?
1.6	Would you be satisfied if an algorithmic decision-making system made decisions based on the criteria you have considered?	2.4	How could such a situation be prevented?
1.7	Are decision-making criteria being applied that cannot be influenced by the applicants themselves?	2.5	Do you consider it justifiable to employ algorithmic decision-making systems in the classification of monkeys? Why or why not?
1.8	Would you personally consider the decisions made to be fair? Why or why not?	2.6 / 2.8 / 2.10	Regarding S1 / S2 / S3: Which decision-making criteria may have been used by the algorithmic decision-making system? Which of these can be influenced by the applicants themselves?
1.9	What impact would the use of such an algorithmic decision-making system have in the respective situations? Would you support its implementation?	2.7 / 2.9 / 2.11	Regarding S1 / S2 / S3: Do you consider it justifiable to employ an algorithmic decision-making system in this situation? Why or why not?
1.10	For what reason might a decision-making system trained on historical data employ criteria that you would deem unfair?	2.12	Would you also employ such systems in other contexts? If so, in which ones and why (or why not)?
1.11	How could such an issue be mitigated?		
1.12	Would you support the use of the system if certain changes were made?		
1.13	Algorithmic decision-making systems utilize historical data to make decisions about future outcomes. Discuss in your small groups the potential opportunities and risks of such an approach.		

ANALYSIS OF REFLECTION PROCESSES

In the two implementations of the seminar concept presented above, the reflection processes of the learners are examined. The following research question is pursued: To what extent do learners' reflections demonstrate context relevance? And how does this differ between the two design experiment cycles?

Method

The students answered the reflection tasks (Table 2) in writing. The first implementation of the material took place within the framework of a seminar for students enrolled in the mathematics teacher education program for secondary schools conducted by Katja Lengnink at the Justus Liebig University Giessen during the winter term 2022/23 (see Büscher & Lengnink, in press). The material presented above covered one session (90 minutes) of the seminar. Twenty-one students, divided into four groups of four and one group of five, participated in the session. In the second implementation the material covered two sessions (each 90 minutes) of a seminar for students which were also enrolled in the mathematics teacher education program for secondary schools (conducted by the authors at University of Cologne, winter term 2024/25). The reflection tasks were completed by 7 groups which consisted of two to four members (four groups of two, two groups of three, and one group of four). The written responses of the students were subsequently examined for context relevance.

An answer was classified as “context-related” if it did not solely refer to the model, the base, or the decision but mentioned some form of context (society, personal life world, etc.). An example of this coding can be seen in Table 3. The number of context references in the answers was counted for each iteration of the seminar and compared proportionally. Additionally, the responses were analysed qualitatively.

Table 3. Example coding (translated from German)

Question	What are the consequences if an incorrect decision results from the classification of a monkey?
Context-related answer	“That a zookeeper could be bitten.”
Abstract answer	“That the decision tree exhibits errors or lacks accuracy.”

Results

In the responses to the 13 reflection tasks in the first realisation of the seminar, a context reference is found 40 times, and no context reference appears 20 times. This results in a rounded percentage of 67% context-related answers versus 33% abstract answers. In the second iteration of the seminar, the 12 reflection tasks were answered with context relevance 66 times (81%) and without 15 times (19%). Therefore, a higher proportion of context-relevant answers is found in the second iteration (see Figure 2). This indicates that in the second iteration, students were more likely to incorporate context into their reflections compared to the first iteration of the seminar.

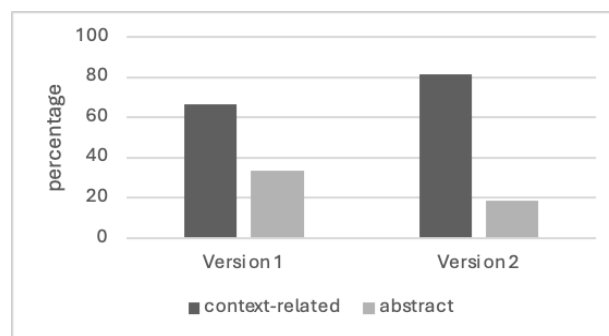


Figure 2. Responses with and without context relevance in both iterations (percentages)

A closer examination of the students' responses reveals that, in some cases, comparable questions elicited differing numbers of context-related answers across the two versions, and that these references varied in their level of detail. In response to the question concerning the significance or consequences of an incorrect decision resulting from the classification of monkeys (Table 2, items 1.3 and 2.2), and how such a situation could be prevented (Table 2, items 1.2 and 2.4), the first iteration of the seminar concept predominantly features answers referring to the model itself; in the second iteration, more context-related references are provided. Examples can be found in Table 4.

Table 4. Responses from group 5 (version 1) and group 2 (version 2) to two reflection tasks (translated from German)

Version 1	Version 2
What is the significance of an incorrect decision emerging because of the classification of a monkey?	What are the consequences if an incorrect decision results from the classification of a monkey?
“Algorithm too inaccurate; insufficient data / categories.”	“The zookeeper could be unexpectedly bitten because he is careless and assumes that the monkey will not bite.”
How could such a situation be prevented?	
“Collect more data.”	“To avoid false negative decisions that could endanger the zookeeper, one should assume that the monkeys will bite when encountering new features, in order to err on the side of false positive decisions, thereby reducing the risk of being bitten.”

In response to the question of whether it is considered justifiable to employ algorithmic decision-making systems in the classification of monkeys (Table 2, items 1.4 and 2.5), it becomes

evident how differently the contextual references are elaborated in the two versions. While in the first iteration, only brief context-related answers are found, the second iteration presents numerous arguments explained in detail. Examples can be found in Table 5.

Table 5: Responses from group 2 (version 1) and group 2 (version 2) to a reflection task (translated from German)

Version 1	Version 2
Do you consider it justifiable to employ algorithmic decision-making systems in the classification of monkeys? Why or why not?	
“It can be used but should be considered on an individual basis.”	“The categorization can be provided to the zookeepers as a guideline, but the keepers should generally not rely on it. Instead, caution should always be exercised during feeding. The characteristics do not directly indicate the behaviour of the monkeys – the decision is based on statistical probabilities. All new monkeys would always have to be classified as biting, even if they are not dangerous, which would be unfair to these monkeys.”

DISCUSSION, LIMITATIONS AND OUTLOOK

Future teachers face the challenge of preparing their students for the implications of the omnipresence of AI. This can and should also take place in mathematics education – specifically by deliberately fostering reflection that extends beyond the immediate mathematics itself (Skovsmose, 1998; Jablonka, 2003; Lengnink, 2006). Learning opportunities on the topic of AI in mathematics education should explicitly initiate such reflections. This article examines two versions of a seminar concept with respect to how contextual references in students’ reflection processes differ.

The analysis of the learners’ reflection processes shows that, in the second iteration of the seminar, a higher proportion of responses included a reference to a context, and the references to context were more diverse. These results may suggest that concrete connections to the learners’ everyday lives help to promote more context-aware reflections (it should be noted that the references to everyday life in the introduction and the excursion in the second version were somewhat disconnected from the rest of the learning environment). The inclusion of social media topics might have triggered a deeper understanding among the learners. In a final survey, students mention that their understanding of why certain content is shown to them on social media platforms has increased and that it prompted them to reconsider their usage.

This conclusion drawn from the results should be treated with caution, as the setting of the two versions of the seminar varied in many factors, such as the instructors, the duration of engagement with the material, and the students. For instance, the final survey after the second iteration of the seminar revealed that some students were already familiar with various aspects of the technologies and their impacts. It was explicitly mentioned that the topic had already been addressed in another seminar before. This prior exposure could have contributed to the higher number and greater diversity of context references in the second iteration of the seminar.

The presumed connection between specific references to everyday life in the material and more context-related reflections from the learners should be further investigated in future studies. For example, an intervention study that compares both versions in a controlled manner could provide deeper insights like which elements of the seminar can be identified to be the key elements that trigger context-related reflections. Additionally, an initial and final survey could help assess the relevance of prior knowledge and measure changes within a single use of the material.

It should be noted that the material’s development is at a very early stage. The two implementations give rise to numerous ideas for further development. Concerning foundational concepts, decision rules for the branching of decision trees – such as the Gini index – could be explained, thereby establishing a connection to probability theory. Furthermore, algorithmic thinking could also be fostered by integrating a “plugged” element into the session, as pursued, for example, in the project www.prodabi.org. In order to create an immediate point of connection to the students lived experiences, both the scenario of the biting monkeys (Figure 1A) and the real-world situations (Table 1) could be

replaced with topics more closely related to everyday life of the learners. In addition, the elements introduced in the second iteration of the seminar could be more effectively linked to the pre-existing components of the material. Another approach that supports students in connecting theoretical concepts to their everyday lives and fosters their competency in navigating the digital world is presented by Höper et al. (2024) with so-called “explanatory models”. The authors additionally develop an analysis tool to study the empowerment gained by students after the intervention. Both the approach for material development and the analysis tool could be incorporated into further developments of our seminar concept and the associated research on reflection processes.

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