“I Think I Would Rather Decide What to Do”: Students’ Perception of Control in an AI-Infused Classroom

Martina Vincoli[1[0009-0004-0706-9470]], Niklas Scholz[2[0009-0007-5754-6011]], Tomohiro Nagashima[3[0000-0003-2489-5016]]

[1]Department of Humanities, Social and Political Sciences, ETH Zürich, Zürich, Switzerland
martina.vincoli@gess.ethz.ch
[2]RWTH Aachen University, Aachen, Germany
niklas.scholz@rwth-aachen.de
[3]Saarland University, Saarland Informatics Campus, Saarbrücken, Germany
nagashima@cs.uni-saarland.de

Abstract. Artificial Intelligence (AI) has increasingly been integrated into school classrooms to optimize human learning. However, prior studies do not yet offer a complete understanding of students’ experiences and preferences for learning with AI in the classroom, specifically regarding the desired degree of control as AI systems begin to automate important decision-making opportunities. We conducted a qualitative speed-dating study with 16 secondary-school students to investigate their preferences for control in an AI-augmented classroom. Our findings reveal that students’ desire for control is not uniform; rather, it fluctuates based on the specific type of decision being made. Our work demonstrates the importance of understanding students’ sense of control as a multi-dimensional concept and its dynamic nature involving how students view their teacher and AI, rather than a single-dimensional, static concept. Based on our findings, we provide design recommendations for future classroom AI systems.

Keywords: Intelligent Tutoring Systems, AI, Decision-making, Control, Design study.

1 Introduction

Artificial intelligence (AI) is becoming an integral part of our everyday lives, and education is no exception. AI-based learning technologies, such as Intelligent Tutoring Systems (ITSs), offer adaptive support for students such that the system can provide the most optimal content, scaffolding, and feedback based on its understanding of each student’s mastery and knowledge status [1–3]. While AI-based, intelligent learning software has been shown effective in enhancing learning [4], its efficacy does not necessarily guarantee ethical or meaningful use that meets stakeholders’ needs and desires. Despite a rise in participatory design approaches in addressing stakeholder needs and desires [5], K-12 students remain largely excluded from the development of classroom AI, which typically prioritizes teachers as the primary user group [6–9]. This exclusion of students is concerning, as students are central stakeholders whose perspectives on data privacy and control often diverge significantly from those of their teachers [5]. In particular, students' perspectives on how much control to exercise during learning with AI in the classroom environment have gained limited attention [10, 11].

In this work, we address the following research question: *What are students' preferred levels of control when learning with AI systems in the classroom?* We conducted a speed-dating study [6, 12] with 16 secondary-school students in Germany to address the question. Speed dating is a design method in which users react to a variety of stimuli, in this case hypothetical AI technology use in the classroom, to understand how participants react to possible technology use cases [12]. Our findings show that students prefer varying levels of control over different kinds of decisions when learning with AI in the classroom, revealing the multi-dimensional nature of their sense of control. We also found that these preferences are shaped by how students perceive other key decision makers in the classroom (i.e., teachers and AI), showing the importance of dynamic interactions among all agents in the learning environment. This work contributes to the field of technology-enhanced learning by offering empirical evidence that students' desired level of control cannot be understood as a single construct but rather as shifting negotiations across multiple dimensions in the complex classroom environment.

2 Related Work

Prior research on youth and AI has typically been conducted outside of school classrooms (e.g., voice assistants at home). This line of research highlights that youth often perceive AI as social beings, either scary or trustworthy, attributing human-like traits to conversational agents [13, 14]. While these studies show how to achieve effective youth-AI collaboration (e.g., through turn-taking and shared goals [15, 16]), classroom dynamics are more complex. Classroom interactions are mediated by peers and teachers who intervene in and influence the student-AI relationship [17–20]. Consequently, perceptions of control in other contexts may not directly transfer to the classroom environment.

In the context of K-12 school classrooms, studies have proposed and documented how AI could be used to enhance effective collaborations among stakeholders (i.e., students, teachers, and AI technologies as decision-making agents). For example, while early work on ITSs conducted classroom evaluations without paying particular attention to the teacher's role, the focus has shifted toward an *empowerment* view, emphasizing collaboration between humans and AI in supporting student learning [10, 11, 15, 21, 22]. In line with this shift, Molenaar's [22] framework illustrates varying levels of teacher-AI reliance in the classroom, such as "conditional automation," where AI would lead instruction while teachers would monitor it. This paradigm highlights how AI can complement human teaching rather than substitute for it [9, 23].

However, current *hybrid intelligence* (i.e., combining human intelligence and artificial intelligence) [22] or *humans in the loop* (e.g., incorporate people's viewpoints in the design and development of tools) [9] research in K-12 classrooms primarily focuses on teachers, leaving out students' perspectives [22]. While recent studies have captured students' perspectives towards AI, most of these studies are typically concerned with either higher education environments [11]. We consider K-12 classroom dynamics to be complex yet meaningful environments for AI interaction that warrant investigation, particularly as we currently lack a holistic view of the student experience [19]. Students and teachers frequently have diverging needs and privacy preferences regarding AI use [6, 19]. Addressing this literature gap in students' perspectives of AI use in K-12 classrooms is essential for designing systems that respect student desires and align design with their specific goals [10].

In particular, student control, which we refer to as the autonomy and decision-making power exercised during technology-enhanced learning, is a central factor in classroom AI adoption. While prior research often implicitly assumes that higher control yields better outcomes for students [24], empirical evidence is mixed; some studies found that higher decision-making control leads to improved learning, while others suggest restricted control can scaffold students well and produce higher gains despite lower engagement [11, 24]. Critically, students' decision-making control in these prior studies has primarily been simplified as a one-dimensional metric of *high vs. low* [25]. Following recent work by Vincoli [26], who proposed a multi-dimensional framework of student agency in classroom decision-making, we consider that student control spans multiple aspects of decision-making opportunities in the classroom. Specifically, beyond just choosing (or having AI choose) what to learn (Content Control) [26], students might decide on what data to share and with whom (Data Control) [10, 26, 27], when and with whom to collaborate in the classroom (Orchestration Control) [23, 26-28], and the level of assistance they receive in the classroom (Help & Feedback Control) [26, 29]. The mentioned dimensions of control are illustrated in Table 1. Past studies have not fully investigated students' views on these critical aspects of decision-making in the classroom environment. The multi-dimensional understanding of student-AI control is critical for identifying where standardized AI metrics may generate unfair and inappropriate decisions; AI systems that rely on one-size-fits-all quantitative indicators can oversimplify complex human behavior and penalize specific personality traits [11].

3 Methods

To better understand students' perspectives on decision-making control in the AI-supported classroom, we conducted a speed-dating study in Germany. Our research question (RQ) asks: *What are students' preferred levels of control when learning with AI systems in the classroom?*

3.1 Participants

We recruited 16 students from German secondary schools with a mean age of 14 years old (more details can be found in Table 2). We specifically targeted secondary-school students, as secondary schools are often a strong focus for digitalization initiatives in

Germany[1]. Participants were recruited either through their school or through prior contacts in the lab. Participants were given the option to choose the language of participation (German or English). The study had been approved by the third author's university's ethical review board prior to data collection, and each participant was given an informed consent, which their parents or legal guardian signed. Participation was fully voluntary. Participants were compensated with 12 euros upon completion of the study.

Table 1: Multi-dimensional student control in learning with AI in the classroom

Control Dimension	Description	Example decision-making situation	
		When a learner has more control	**When an AI system has more control**
Help & Feedback Control	Control on how much help (e.g., scaffolding) and feedback learners request/need/want vs. what AI provides during learning	A learner spontaneously asks for hints from an AI system when they want help.	An AI system provides feedback when it detects learners' consecutive incorrect attempts in the system.
Data Control	Control on how much learning data learners share with the AI system (vs. AI collects) and with whom (e.g., teacher)	A learner chooses not to share their learning data with their teacher.	An AI system automatically sends learners' data to their teacher without notifying learners.
Orchestration Control	Control on how much and with whom to work on collaborative activities in the classroom	A learner picks whom to work with on a collaborative learning task.	An AI system determines group assignments based on the performance of the learners.
Content Control	Control on what and how much content to work on in an AI-based learning system	A student chooses to work on problems that they have practiced already.	An AI system assigns a student a difficult problem based on its understanding of the student's mastery.

3.2 Materials

With the goal of grounding stakeholder views in a specific context, we developed a set of materials to capture insights tailored to AI-supported classroom interactions. Specifically, we created eight storyboards (referred to as scenarios in this paper) depicting concrete interactions that may occur in classrooms that involve AI systems and teachers. To elicit student insights, we developed scenarios spanning four

[1] https://www.digitalpaktschule.de/de/digitalpakt-2-0-1874.html

dimensions of control proposed by Vincoli [26], each instantiated through two extreme cases: *full student control* and *full AI control*. In total, we created eight scenarios (four dimensions × two versions). For each scenario, we then designed two possible endings: one positive and one negative (Figures 1 and 2). For example, Figure 1 illustrates two outcomes under full student control over homework assignment (Content Control): successful (positive) test preparation (4A) and insufficient (negative) preparation (4B), depending on the student's decision. Similarly, Figure 2 presents outcomes under full AI control over homework assignment: in 4A, the student is satisfied with an appropriate assignment (positive), whereas in 4B, students discuss a perceived unfair outcome (negative).

Table 2: Participants' demographics including reported AI tools they are familiar with. Google Services includes services such as Google Lens and Google Assistant. "-" indicates that the participant did not name any AI tool they had used before.

Participant ID	Age	Grade level	Known/Used AI Tools
P1	16	11th	ChatGPT, Dall-E
P2	16	10th	Siri, Alexa, Snapchat AI
P3	12	6th	ChatGPT, Bing AI, Crayon AI, Google Services
P4	14	8th	ChatGPT, Snapchat AI,
P5	12	6th	-
P6	14	7th	Translator
P7	13	7th	-
P8	17	11th	ChatGPT, Dall-E,
P9	12	6th	ChatGPT
P10	16	10th	ChatGPT, Translator
P11	13	8th	ChatGPT, Google Services
P12	12	7th	ChatGPT
P13	16	10th	ChatGPT
P14	18	12th	ChatGPT, Google Services
P15	12	6th	-
P16	14	8th	-

These scenarios were selected and designed based on prior design-based studies using storyboards to investigate classroom AI use [6, 17] and empirical studies testing multiple control dimensions [29]. We used contrasting outcomes to capture how students' views vary based on the results of AI use (because showing only positive or negative endings would bias their views). We chose to provide such scaffolding materials since the use of AI-based tools and digital tools was still in a very early stage in German schools at the time of data collection (therefore, it would have been difficult for school-aged children to imagine what AI could do) [29, 30]. Prior work has used storyboards as an effective way to elicit deep insights into how teachers and students think about the use of AI technology in the classroom [6, 23]. All eight scenarios are available online[2].

3.3 Procedure

Participants attended the study either online or in-person. In total, 13 participants chose the online option; the other three were interviewed at the university. Each session took 45-60 minutes. Two researchers joined each session, where one researcher facilitated the study and the second researcher took notes and asked further questions if needed. The eight scenarios were presented in a randomized order to minimize the order effect. They were presented in English or German, depending on the language of choice. All sessions were video recorded for later analysis, except for one where consent was given only for taking written notes.

To capture students' contextualized view toward agency when interacting with AI, we designed study materials that are aimed at eliciting their deep insights into the topic. Specifically, we designed an interview protocol where students would be introduced to the study comfortably, starting with warm-up questions about their school environment, and then onto the topic of AI, letting them freely express their thoughts as they wanted. We asked seven main questions in total (e.g., "What do you do when you don't understand something in class? and "Have you ever used an AI tool?," also see Table 2). We intentionally designed it as a semi-structured interview, as the main purpose was to help participants feel comfortable in sharing their honest thoughts in the session.

[2] https://tinyurl.com/ectelstudentscenarios

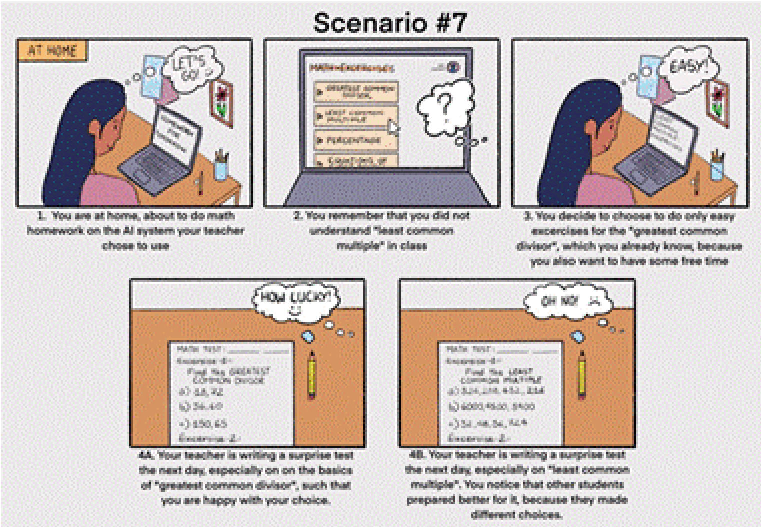

Fig. 1. Scenario with full student control over their homework assignment; the student chose to work on easy tasks they already know. A positive ending (4A) shows that the teacher assigns a test on the practiced topic, while a negative ending (4B) shows that their choice did not match what the teacher assigns (Content Control - full student control).

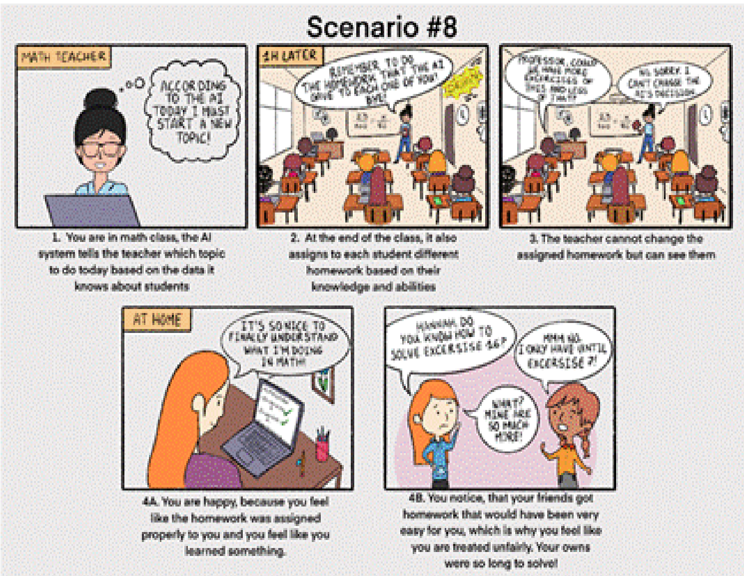

Fig. 2. Scenario with full AI control over assignment; the AI assigns students different homework based on each one's knowledge state. A positive ending (4A) shows that the assignment matched the student's level of understanding, a negative ending (4B) shows the student feeling unfairly treated due to such differences (Content Control – full AI control).

3.4 Analysis

We gathered and machine-transcribed approximately 14 hours of video recordings, which, where necessary, were adjusted or translated from German into English. The transcribed interviews were first analyzed using a thematic analysis, following a hybrid deductive-inductive approach. Specifically, we utilized a coding rubric based on the four dimensions of control to deductively categorize the data. Researchers extracted segments from the transcripts into discrete codes (labels and short descriptive sentences), which were then synthesized using the Affinity Diagramming method [31]. Affinity Diagramming is a technique that allows researchers to collaboratively group codes into emergent themes. We iteratively refined our original assumptions to ensure that the analysis was both theoretically structured by Vincoli's framework [26] and flexible enough to capture bottom-up insights from the participants.

We first organized codes following the original study interview structure (Fig. 3a). A total of 644 codes were developed using the deductive approach (described above), which were then placed onto the whiteboard (Fig. 3b). Using the 644 initial codes, we first conducted Affinity Diagramming *horizontally* (i.e., finding common themes across participants within each topic, Fig. 3c). Then, we performed Affinity Diagramming *vertically* (i.e., looking for common themes across different topics) to find common codes across the different sub-parts of the interview (Fig. 3d). Finally, we re-organized resulting theme categories based on commonalities to formulate high-level themes.

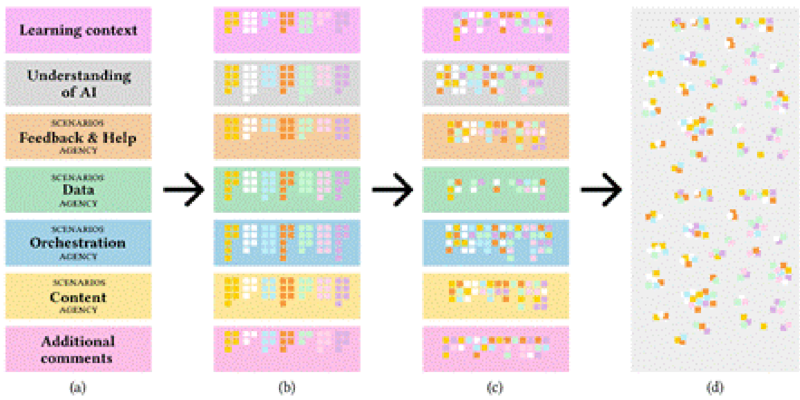

Fig. 3. Visualization of the analysis process: (a) shows the interview procedure that we followed (from top to bottom). We first structured codes following the interview procedure (b), then organized codes within each part of the study procedure (c). Then, we looked across the categories and formed themes across all categories (d).

4 Results

The Affinity Diagramming process produced a total of three high-level themes and 30 low-level themes. The three high-level themes are described in the following sections.

4.1 Students' Perceived Control in AI-Supported Learning Differs Across Types of Learning Decisions

First, we found that students generally expressed a desire to retain control over learning decisions. This preference was particularly strong regarding Data Control, with some students viewing their learning data as a direct representation of themselves ("[The data] is what I am," P1). For most, it was important to establish clear boundaries around who could access this information ("[learning data] should be your opinion and you should not be forced to show [it to] everyone," P13). AI-driven data collection and monitoring were often perceived as unsettling or judgmental, with students describing feelings of anxiety and pressure ("I'd be more anxious about seeing the teacher on the next day," P14; "You always have this pressure in the back of your mind that you can't make a mistake," P8; "If you struggle on one task, [...] it ruins your complete stats, then you feel very bad about it," P1). As a result, many expressed reluctance toward extensive AI monitoring of their learning activities.

In contrast, students felt less confident in making decisions about content assignments (Content Control) and generally preferred these decisions to be made by a more knowledgeable agent. They believed that many students would choose easier tasks for convenience ("I can see a lot of students just picking the easier way just because they want more free time or something," P15), and therefore trusted either their teachers or AI systems to make more appropriate decisions. Many also recognized AI's ability to gradually adapt tasks to individual performance levels, and thus make better learning choices for them in the long run, showing a preference on delegating their decision-making control over to AI long-term ("If you get tasks adapted to your performance level, that is perfect, and if the topic is adapted to the performance level of the class, I think that is also great," P8).

The remaining control dimensions revealed more nuanced preferences. Regarding Help & Feedback Control, students expressed a balanced view of the appropriate level of AI involvement. Some students favored AI-driven control to overcome the limitations of human teachers, viewing AI as a personal tutor for every student ("We can learn a lot of things because the teacher can never see every problem, and an artificial intelligence can do this because AI is like for every student one teacher," P10). Others, however, viewed human teachers as irreplaceable, arguing that AI hints lack the contextual, nuanced understanding of a teacher's intuition ("When you talk with a person […] they see if you're understanding it, and if not, they can help you and with this [AI-generated] hints, you just do not understand it really well," P13). Overall, students advocated for a collaborative approach in which AI-generated learning analytics empowers teachers to identify difficulties and provide targeted instruction ("if your data shows that this is a topic a lot of students struggle with, then the teacher can just help a lot more," P14; "I would share [with] my teacher [...] because they could help," P16).

For Orchestration Control, students generally appreciated AI's ability to manage organizational aspects of learning but considered that social dynamics among peers are complex, and an AI would not be able to capture them accurately. As one student summarized, "[AI] just doesn't get [interactions]," P13.

4.2 The Tension Between Students' Understanding of AI and Their Trust in It

Beyond their desire for control, we found that students' views on AI varied depending on their experience with and knowledge of AI. Most viewed AI as a functional tool "for writing texts, for spell checking or [when] you need help with the structure of some texts," (P8) or that "[gives] answers quite quickly on the basis of information," (P13), or a tutor that "would kind of give you feedback on its own" (P14). Few offered slightly more technical definitions, describing it as "just a mathematical function" that "adapts and learns" (P1). The observed variation in students' understanding of AI likely reflects differences in their prior exposure to AI. It also seems that these differences, in turn, appeared to shape where students placed their trust. Although AI was generally perceived as beneficial, some students who lack a complete understanding of AI expressed concerns that relying on it too heavily could negatively affect their own learning ("Disadvantages are probably that you don't learn anything yourself," P4).

This variability in preferences for the appropriate level of control led to divergent views on automated personalization. While some viewed AI-based adaptation of task difficulty as "perfect," others expressed concerns about feeling "unfairly treated" (P8). Skepticism toward AI-assigned tasks often stemmed from concerns about "gaming the system" [11, 32], with students sharing that the absence of human oversight could encourage behaviors such as "just click[ing] on all the hints" (P1) rather than meaningfully engaging with the assigned tasks.

Also, students viewed teachers as irreplaceable sources of authority and oversight in an AI-infused classroom environment: "I think the teacher should always be there because AI won't be perfect" (P1). Regardless of AI-generated recommendations, students emphasized that teachers should retain final decision-making power, citing teachers' superior skill to understand students as individuals: "I think [the AI] is able to do this but I would give it to the teacher [...] because I think a human [...] knows you better" (P11). This strong trust in human teachers may reflect participants' limited experience with AI learning systems, but it nevertheless highlights the critical role teachers continue to play in students' perceptions of AI-supported instruction. For these students, the right level of control is one where the AI handles task generation, but the human teacher maintains the moral and pedagogical authority to validate the outcome.

4.3 Social Factors Influencing Safe and Effective AI Use in Learning

The study also provides an initial view of how classroom social dynamics may be influenced by the presence of a new intelligent agent, such as an AI-powered tutor. For instance, although students generally showed a positive view towards getting help from peers, they expressed contrasting thoughts when it comes to peer involvement in personal data, causing embarrassment: "if you don't understand something, you feel a little bit bad and the teacher goes to you […] and you think that everybody is looking at you" (P11) and "When your grades aren't that good and you're embarrassed in front of your teacher or your parents" (P13). This suggests that AI-supported learning may intensify the social visibility of individual performance, with critical implications for students' emotion and privacy.

5 Discussion

5.1 Key Findings

Prior research rarely consults students on the optimal integration of AI into classroom learning, despite their unique and important perspectives as the primary users of AI systems. We conducted a design-based study with 16 German secondary-school students to investigate their views on AI use in school classrooms. Our study reveals that students' preferences for learner-AI control are highly situational; for instance, participants strongly preferred retaining Data Control, emphasizing ownership and autonomy over their data. On the other hand, they were more willing to delegate Content Control as they recognized the limitations of their own metacognitive decision-making skills and value AI's ability to personalize learning.

Beyond these dimension-specific preferences, the study also suggests dynamic interactions and control negotiations among students, AI systems, and teachers in making important decisions in the classroom. Students' trust in AI varied according to their familiarity with AI technologies, illustrating the individual differences in how much they could accept AI-driven personalization. At the same time, students consistently regarded teachers as the ultimate decision-makers in AI-supported classrooms. Participants valued teachers' skills in understanding students as individuals and providing oversight beyond AI capabilities. This finding reflects students' trust in teachers; students tended to view AI as a supportive assistant rather than an autonomous authority, whose recommendations should remain subject to teacher decisions.

These findings underscore that student-AI control in the unique classroom context cannot be reduced to a single high-vs.-low dimension. Instead, it needs to be understood as multi-dimensional and dynamic interactions between individual students, AI, and teachers. Based on these insights, we propose design recommendations for future AI-based TEL systems for classroom use.

5.2 Design Recommendations for Future Classroom AI Systems

Our findings suggest that a static approach to designing AI-based classroom systems would fail to account for the diverse and dynamic control preferences of students. We argue that future systems must transition from fixed automation to adaptive control interfaces that allow for granular user adjustment, thereby considering students as decision-makers in the classroom [19]. For example, rather than designing a system that assumes and determines the *appropriate* level of support, the interface could incorporate *scaffolded choices* inviting students to decide between receiving an answer, receiving a problem-solving hint, solving the problem independently, or asking their teacher for help. Such an explicit choice-making mechanism could help address the tension we observed between students' desire for efficiency and their concerns about "gaming the system" by allowing them to regulate their cognitive load and help-seeking behavior.

To further address the unsettling feelings that students would have toward AI surveillance and monitoring, future systems could integrate student-facing privacy dashboards. These dashboards would provide a transparent visualization of the data being tracked and clearly state which data are accessible to the teacher (and other stakeholders) [10, 33]. By making data-sharing settings explicit and adjustable, systems can transform the feeling of being watched into an experience of being supported, aligning with research that prioritizes student-led control in Open Learner Models [3, 34]. Also, these preferences may evolve with experience and growing technical fluency; therefore, systems should incorporate periodic preference reassessment cycles to accommodate changing needs.

Finally, while current participatory design practices for K-12 classroom AI tools predominantly focus on teachers, having students in the design process would reveal unique insights and inspire novel features, such as motivational virtual agents that explain system logic. Student-centered design processes ensure that classroom AI tools are not only effective but also safe, ethical, and meaningful [11].

5.3 Limitations

We acknowledge several limitations of the study. First, the small sample size, with a sparse age distribution, limits the generalizability of these findings. Second, the cultural context of the study, i.e., Germany/Europe, likely shaped participants' perspectives. Cultural norms regarding data privacy, institutional trust, and the role of automation in society vary significantly, and our findings may reflect a specific viewpoint on student-AI control negotiation. Also, given the voluntary nature of the study, the participants might not represent the general population of German K-12 students. Finally, even though the materials we used in the study (i.e., hypothetical scenarios of AI use) were designed based on prior work, the eight scenarios may not fully represent what would happen in German classrooms in the future.

6 Conclusion

Despite a growing interest in AI systems for classroom use, students' perspectives on student-AI interactions are not sufficiently represented in the literature. We conducted a qualitative study with 16 secondary-school students in Germany to understand their perspectives, focusing on how much control they would desire when learning with AI. Our findings showed the complexity of students' sense of control in AI-student interactions that encompass multiple dimensions of decision-making opportunities. We provide design recommendations for future classroom AI systems such that designers and researchers can meaningfully address and respect students' sense of control in their deign practice. Future studies can investigate how the insights we found might look different/similar in other contexts.

Acknowledgments

We thank all the students participating in the study.

References

1. Wu, R., Yu, Z.: Do AI Chatbots Improve Students Learning Outcomes? Evidence from a Meta-analysis. Br. J. Educ. Technol. 55, 10–33 (2024). https://doi.org/10.1111/bjet.13334.
2. Urban, M., Děchtěrenko, F., Lukavský, J., Hrabalová, V., Svacha, F., Brom, C., Urban, K.: ChatGPT Improves Creative Problem-solving Performance in University Students: An Experimental Study. Comput. Educ. 215, 105031 (2024). https://doi.org/10.1016/j.compedu.2024.105031.
3. Khosravi, H., Shum, S.B., Chen, G., Conati, C., Tsai, Y.-S., Kay, J., Knight, S., Martinez-Maldonado, R., Sadiq, S., Gašević, D.: Explainable Artificial Intelligence in Education. Comput. Educ. Artif. Intell. 3, 100074 (2022). https://doi.org/10.1016/j.caeai.2022.100074.
4. Holmes, W., Tuomi, I.: State of the Art and Practice in AI in Education. Eur. J. Educ. 57, 542–570 (2022). https://doi.org/10.1111/ejed.12533.
5. Holstein, K., McLaren, B.M., Aleven, V.: Designing for Complementarity: Teacher and Student Needs for Orchestration Support in AI-Enhanced Classrooms. In: Isotani, S., Millán, E., Ogan, A., Hastings, P., McLaren, B., and Luckin, R. (eds.) Artificial Intelligence in Education. pp. 157–171. Springer International Publishing, Cham (2019). https://doi.org/10.1007/978-3-030-23204-7_14.
6. Holstein, K., McLaren, B.M. and Aleven, V. 2019. Co-Designing a Real-Time Classroom Orchestration Tool to Support Teacher–AI Complementarity. Journal of Learning Analytics. 6, 2 (Jul. 2019), 27–52. https://doi.org/10.18608/jla.2019.62.3.
7. Lawrence, L., Echeverria, V., Yang, K., Aleven, V., Rummel, N.: How Teachers Conceptualise Shared Control with an AI Co-orchestration Tool: A Multiyear Teacher-Centred Design Process. Br. J. Educ. Technol. 55, 823–844 (2024). https://doi.org/10.1111/bjet.13372.
8. Bond, M., Khosravi, H., De Laat, M., Bergdahl, N., Negrea, V., Oxley, E., Pham, P., Chong, S.W., Siemens, G.: A Meta Systematic Review of Artificial Intelligence in Higher Education: a Call for Increased Ethics, Collaboration, and Rigour. Int. J. Educ. Technol. High. Educ. 21, 4 (2024). https://doi.org/10.1186/s41239-023-00436-z.

9. Cheah, Y.H., Lu, J., Kim, J.: Integrating Generative Artificial Intelligence in K-12 Education: Examining Teachers' Preparedness, Practices, and Barriers. Comput. Educ. Artif. Intell. 8, 100363 (2025). https://doi.org/10.1016/j.caeai.2025.100363.
10. Toth, A., Roch, N., Zufferey, N., Zimmermann, V.: "I Would Share It, But..." Exploring Ways to Optimize the Privacy-Personalization Trade-Off in Intelligent Tutoring Systems. In: Cristea, A.I., Walker, E., Lu, Y., Santos, O.C., and Isotani, S. (eds.) Artificial Intelligence in Education. pp. 68–76. Springer Nature Switzerland, Cham (2025). https://doi.org/10.1007/978-3-031-98462-4_9.
11. Han, B., Coghlan, S., Buchanan, G., McKay, D.: Who is Helping Whom? Student Concerns about AI-Teacher Collaboration in Higher Education Classrooms. Proc ACM Hum-Comput Interact. 9, CSCW206: 1-CSCW206:32 (2025). https://doi.org/10.1145/3711104.
12. Zimmerman, J., Forlizzi, J.: Speed Dating: Providing a Menu of Possible Futures. She Ji J. Des. Econ. Innov. 3, 30–50 (2017). https://doi.org/10.1016/j.sheji.2017.08.003.
13. Williams, R., Park, H.W., Breazeal, C.: A is for Artificial Intelligence: The Impact of Artificial Intelligence Activities on Young Children's Perceptions of Robots. In: Proceedings of the 2019 CHI Conference on Human Factors in Computing Systems. pp. 1–11. ACM, Glasgow Scotland Uk (2019). https://doi.org/10.1145/3290605.3300677.
14. Li, Z., Thomas, T., Yu, C.-L., Xu, Y.: "I Said Knight, Not Night!": Children's Communication Breakdowns and Repairs with AI Versus Human Partners. In: Proceedings of the 23rd Annual ACM Interaction Design and Children Conference. pp. 781–788. ACM, Delft Netherlands (2024). https://doi.org/10.1145/3628516.3659394.
15. Chen, F. Human-AI Cooperation in Education : Human in Loop and Teaching as leadership. Journal of Educational Technology and Innovation 2022, 2 (1). https://doi.org/10.61414/jeti.v2i1.34.
16. Zheng, Q., Tang, Y., Liu, Y., Liu, W., Huang, Y.: UX Research on Conversational Human-AI Interaction: A Literature Review of the ACM Digital Library. In: CHI Conference on Human Factors in Computing Systems. pp. 1–24. ACM, New Orleans LA USA (2022). https://doi.org/10.1145/3491102.3501855.
17. Yang, K.B., Lawrence, L., Echeverria, V., Guo, B., Rummel, N., Aleven, V.: Surveying Teachers' Preferences and Boundaries Regarding Human-AI Control in Dynamic Pairing of Students for Collaborative Learning. In: De Laet, T., Klemke, R., Alario-Hoyos, C., Hilliger, I., and Ortega-Arranz, A. (eds.) Technology-Enhanced Learning for a Free, Safe, and Sustainable World. pp. 260–274. Springer International Publishing, Cham (2021). https://doi.org/10.1007/978-3-030-86436-1_20.
18. Yip, J.C., Ello, F.M.T., Tsukiyama, F., Wairagade, A., Ahn, J.: "Money shouldn't be money!" : An Examination of Financial Literacy and Technology for Children Through Co-Design. In: Proceedings of the 22nd Annual ACM Interaction Design and Children Conference. pp. 82–93. ACM, Chicago IL USA (2023). https://doi.org/10.1145/3585088.3589355.
19. Han, A., Zhou, X., Cai, Z., Han, S., Ko, R., Corrigan, S., Peppler, K.A.: Teachers, Parents, and Students' Perspectives on Integrating Generative AI into Elementary Literacy Education. In: Proceedings of the 2024 CHI Conference on Human Factors in Computing Systems. pp. 1–17. Association for Computing Machinery, New York, NY, USA (2024). https://doi.org/10.1145/3613904.3642438.
20. Luo (Jess), J.: How does GenAI affect trust in teacher-student relationships? Insights from students' assessment experiences. Teach. High. Educ. 30, 991–1006 (2025). https://doi.org/10.1080/13562517.2024.2341005.
21. Yan, L., Greiff, S., Teuber, Z., Gašević, D.: Promises and Challenges of Generative Artificial Intelligence for Human Learning. Nat. Hum. Behav. 8, 1839–1850 (2024). https://doi.org/10.1038/s41562-024-02004-5.

22. Molenaar, I.: Towards Hybrid Human-AI Learning Technologies. Eur. J. Educ. 57, 632–645 (2022). https://doi.org/10.1111/ejed.12527.
23. Yang, K.B., Echeverria, V., Lu, Z., Mao, H., Holstein, K., Rummel, N., Aleven, V.: Pair-Up: Prototyping Human-AI Co-orchestration of Dynamic Transitions between Individual and Collaborative Learning in the Classroom. In: Proceedings of the 2023 CHI Conference on Human Factors in Computing Systems. pp. 1–17. Association for Computing Machinery, New York, NY, USA (2023). https://doi.org/10.1145/3544548.3581398.
24. Snow, E.L., Allen, L.K., Jacovina, M.E., McNamara, D.S.: Does agency matter?: Exploring the impact of controlled behaviors within a game-based environment. Comput. Educ. 82, 378–392 (2015). https://doi.org/10.1016/j.compedu.2014.12.011.
25. Guo, L., Wang, D., Gu, F. et al. Evolution and trends in intelligent tutoring systems research: a multidisciplinary and scientometric view. Asia Pacific Educ. Rev. 22, 441–461 (2021). https://doi.org/10.1007/s12564-021-09697-7
26. Vincoli, M., Scholz, N., Nagashima, T.: Multi-dimensional Student Agency in Learning with AI: A Conceptual Framework and Design Implications. In: Cristea, A.I., Walker, E., Lu, Y., Santos, O.C., and Isotani, S. (eds.) Artificial Intelligence in Education. pp. 218–232. Springer Nature Switzerland, Cham (2025). https://doi.org/10.1007/978-3-031-98459-4_16.
27. Holmes, W., Porayska-Pomsta, K., Holstein, K., Sutherland, E., Baker, T., Shum, S.B., Santos, O.C., Rodrigo, M.T., Cukurova, M., Bittencourt, I.I., Koedinger, K.R.: Ethics of AI in Education: Towards a Community-Wide Framework. Int. J. Artif. Intell. Educ. 32, 504–526 (2022). https://doi.org/10.1007/s40593-021-00239-1.
28. Lawrence, L.E.M., Guo, B., Yang, K., Echeverria, V., Kang, Z., Bathala, V., Li, C., Huang, W., Aleven, V., Rummel, N.: Co-designing AI-based Orchestration Tools to Support Dynamic Transitions: Design Narratives through Conjecture Mapping. In: CSCL Proceedings - 15th International Conference on Computer-Supported Collaborative Learning (CSCL) 2022. pp. 139–146. International Society of the Learning Sciences (2022).
29. Nagashima, T., Zheng, B., Tseng, S., Ling, E., & Aleven, V. (2023). Promoting Students' Self-regulated Learning Choices with Diagrams in Intelligent Tutoring Software. In Blikstein, P., Van Aalst, J., Kizito, R., & Brennan, K. (Eds.), Proceedings of the 17th International Conference of the Learning Sciences - ICLS 2023 (pp. 593-600). International Society of the Learning Sciences.
30. The Children's Manifesto for the Future of AI, https://www.turing.ac.uk/news/publications/childrens-manifesto-future-ai, last accessed 2026/06/14.
31. Rosala, M.: How to Analyze Qualitative Data from UX Research: Thematic Analysis, https://www.nngroup.com/articles/thematic-analysis/, last accessed 2026/06/14.
32. Baker, R., Walonoski, J., Heffernan, N., Roll, I., Corbett, A., Koedinger, K.: Why Students Engage in "Gaming the System" Behavior in Interactive Learning Environments. J. Interact. Learn. Res. 19, 185–224 (2008).
33. Zimmermann, V., Toth, A., Sievers, H., Fanconi, L., Isenring, Y., Henz, M., Stöver, A., Gerber, N.: Let's Get Visual - Testing Visual Analogies and Metaphors for Conveying Privacy Policies and Data Handling Information. In: 2025 IEEE Symposium on Security and Privacy (SP). pp. 2303–2321 (2025). https://doi.org/10.1109/SP61157.2025.00240.
34. Bodily, R., Kay, J., Aleven, V., Jivet, I., Davis, D., Xhakaj, F., Verbert, K.: Open Learner Models and Learning Analytics Dashboards: a Systematic Review. In: Proceedings of the 8th International Conference on Learning Analytics and Knowledge. pp. 41–50. ACM, Sydney New South Wales Australia (2018). https://doi.org/10.1145/3170358.3170409.