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Toward Teacher-Centered AI Design: Exploring the Role of Pedagogical Values and Contextual Factors in K-12 Teachers' Perceptions of Responsible AI

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Abstract: Recent advancements in artificial intelligence (AI) offer transformative opportunities for education, yet the alignment between responsible AI principles and K-12 educators' pedagogical values remains unclear, potentially hindering effective teacher-AI collaboration. To address this, we surveyed 98 K-12 teachers to explore their prioritization of five Responsible AI (RAI) principles—autonomy, transparency, safety, fairness, and performance—alongside five pedagogical values—teacher-centered, behaviorism, constructivism, constructionism, and critical pedagogy—across three classroom scenarios: grading, scaffolding science learning, and classroom orchestration. Our findings reveal that educators' pedagogical values significantly influence their RAI priorities, with critical pedagogy aligning with transparency and safety, constructivism with autonomy, and teacher-centered and behaviorism negatively associated with fairness and safety. These results highlight the importance of designing AI systems that accommodate diverse teaching philosophies while addressing potential mismatches, fostering trust, and ensuring equitable integration into K-12 education.

Introduction

Advances in artificial intelligence (AI) are reshaping education by enabling personalized, accessible, and differentiated learning experiences (Chounta et al., 2022; Holmes & Porayska-Pomsta, 2022). However, these advancements raise significant ethical challenges, including concerns about plagiarism (Rößling et al., 2008), bias (Pham et al., 2024), disinformation (Liu et al., 2024), and data privacy (Aly et al., 2024). While policymakers and industry leaders have proposed frameworks for responsible AI (RAI) (Jakesch et al., 2022; Jobin et al., 2019), there is little consensus on their definitions or how they relate to ethical AI. Despite teachers being primary stakeholders in AI adoption within education (Bhimdiwala et al., 2022; Bogina et al., 2021; (Chounta et al., 2022; Holmes & Porayska-Pomsta, 2022), their perspectives on RAI remain underexplored.

K-12 teachers occupy a unique position as both adopters and mediators of AI technologies. They are responsible for protecting students—a particularly vulnerable population—from potential AI-related harms while leveraging these tools to enhance learning outcomes and uphold academic integrity (Abbas et al., 2024; Chounta et al., 2022). This dual role is further complicated by the unpredictable consequences of AI, leading to widespread mistrust among educators and, in some cases, outright bans on AI tools in schools (Bhimdiwala et al., 2022; Nazaretsky et al., 2022). Understanding how teachers perceive and prioritize RAI values is critical to addressing these challenges and ensuring the ethical integration of AI in classrooms. Despite growing interest in the ethical use of AI, research on how RAI principles are understood and applied in educational contexts remains limited. Teachers' pedagogical commitments and the diverse use cases of AI—such as grading (Boe et al., 2013; Code.org, 2024), scaffolding science learning (Perez-Alvarez et al., 2022; Persico & Pozzi, 2015), and classroom management (An et al., 2020; Brunskill et al., 2024; Feng et al., 2023; Yang et al., 2023)—further complicate the landscape. Contextual factors influence how teachers prioritize values like transparency, safety, fairness, and performance, underscoring the need for targeted research that captures their unique perspectives.

This study addresses this gap by investigating how K-12 teachers navigate the ethical implications of AI in education. By examining teachers' pedagogical values and exploring their prioritization of RAI principles across different AI deployment scenarios, this research seeks to inform the design of AI systems that align with educators' values. Understanding these priorities is crucial for fostering trust and ensuring the responsible and effective use of AI in classrooms.

Research question and hypotheses

This study seeks to address the following research question: How do teachers' pedagogical values influence their perceptions of RAI values when integrating AI technologies into classroom instruction? Grounded in Schwartz's value theory and established pedagogical frameworks, this study hypothesizes that teachers' prioritization of RAI values will vary based on their pedagogical values. Specifically, we propose the following hypotheses:

- H1: K-12 teachers who adopt teacher-centered and behaviorism pedagogical values are more likely to prioritize performance in RAI.
- H2: K-12 teachers who adhere to constructivism and constructionism pedagogies are more likely to prioritize autonomy and transparency in RAI.
- H3: K-12 teachers who align with critical pedagogy are more likely to prioritize fairness and safety in RAI.

By examining the interplay between pedagogical values and the prioritization of RAI dimensions, this study aims to provide insights into how educational philosophies shape teachers' perspectives on the responsible integration of AI technologies in classroom settings.

Survey Development

Selecting Responsible AI Values

The selection of fairness, autonomy, safety, performance, and transparency as our focal values is grounded in both existing literature on AI ethics (Jobin et al., 2019) and the specific context of K-12 education (Holmes et al., 2019; Holmes & Porayska-Pomsta, 2022; Chounta et al., 2022; Zawacki-Richter et al., 2019). Moreover, these values consistently emerge as critical considerations in responsible AI development and deployment (Zawacki-Richter et al., 2019), often presenting complex trade-offs in educational contexts (Holmes et al., 2019). For instance, maximizing performance might conflict with ensuring fairness or preserving students' autonomy, while the drive for transparency in AI models might inadvertently compromise safety. Thus, our exploratory study offers a pioneering examination of how K-12 teachers prioritize essential responsible AI values in the context of AI integration in education.

Selecting Pedagogical Values

We focus on five pedagogical values—behaviorism, teacher-centered learning, constructionism, constructivism, and critical pedagogy—to capture the diversity of teaching approaches in K-12 education and their influence on perceptions of RAI. Behaviorism emphasizes structured, measurable outcomes and the use of reinforcement to guide learning. Teacher-centered learning prioritizes the teacher's role in managing instruction, delivering content, and maintaining authority in the classroom. Constructionism promotes hands-on, experiential learning, encouraging students to actively create and explore. Constructivism focuses on collaborative knowledge-building through prior experiences and social interaction. Finally, critical pedagogy emphasizes equity, critical thinking, and linking education to students' lived experiences. By examining these frameworks, we aim to understand how teachers' pedagogical values shape their expectations of RAI technologies.

Survey design

Our survey underwent iterative development to ensure its theoretical alignment, clarity, practicality, and effectiveness in communicating with K-12 teachers. This process included reviews by a professor of philosophy who studies ethics and human values, think-aloud pilots with four educators, and content validation with undergraduate research assistants. The final survey design, as illustrated in Figure 1, consisted of the following components:

- Phase I: Collection of Demographic and Classroom Factors
  After obtaining consent, we gathered data on teacher demographics, teaching expertise, and classroom composition. From these responses, we selected representative variables for the linear regression model used in our analysis. Some demographic factors, such as gender, political orientation, and race/ethnicity, were excluded due to significant skewness (e.g., the majority of participants were white and female), reflecting the homogeneity of the U.S. K-12 teaching profession and the regional context of data collection (Midwestern United States). To address this limitation, future iterations of the study will oversample underrepresented demographic groups to ensure greater diversity.
- Phase II: Collection of Pedagogical Values
  Participants responded to six questions, including four ranking questions and two single-selection questions, designed to measure their alignment with five pedagogical values. The options for these questions corresponded to varying degrees of emphasis on each pedagogical value. Responses were

converted into scores, with each participant receiving a fixed score representing their alignment with each pedagogical framework, as shown in Figure 3 (left).

As previously mentioned, to contextualize the abstract concept of RAI values and explore how nuanced scenarios influence teachers' priorities, participants were randomly and equally assigned to one of three specific AI deployment scenarios, as shown in Figure2, including SciAI (an AI-based science instruction tool; N = 23), OrchestrateAI (an AI-based classroom management tool; N = 22), and GradeAI (an AI-based grading tool; N = 23). After the scenario assignment, participants responded to a set of 10 questions designed to examine their priorities for five RAI values: transparency, fairness, safety, autonomy, and performance.

- Phase III: Responsible AI Values Elicitation
  Each value was assessed through two types of questions: a Likert-scale question, where participants rated the importance of each value based on non-technical descriptions, and an action-oriented question, where they selected a response to a hypothetical issue within their assigned scenario. This design allowed us to investigate how teachers prioritize RAI values both ideally and in real-world-like contexts, providing insights into how these values influence their decision-making.

Figure 1

Survey Design Flow

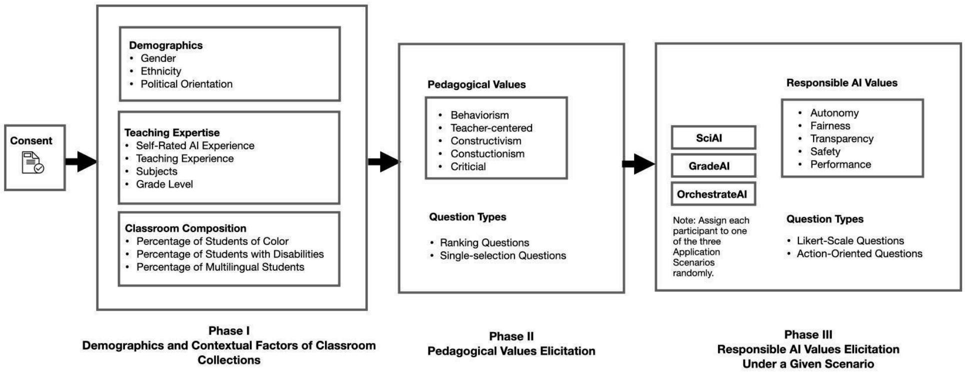
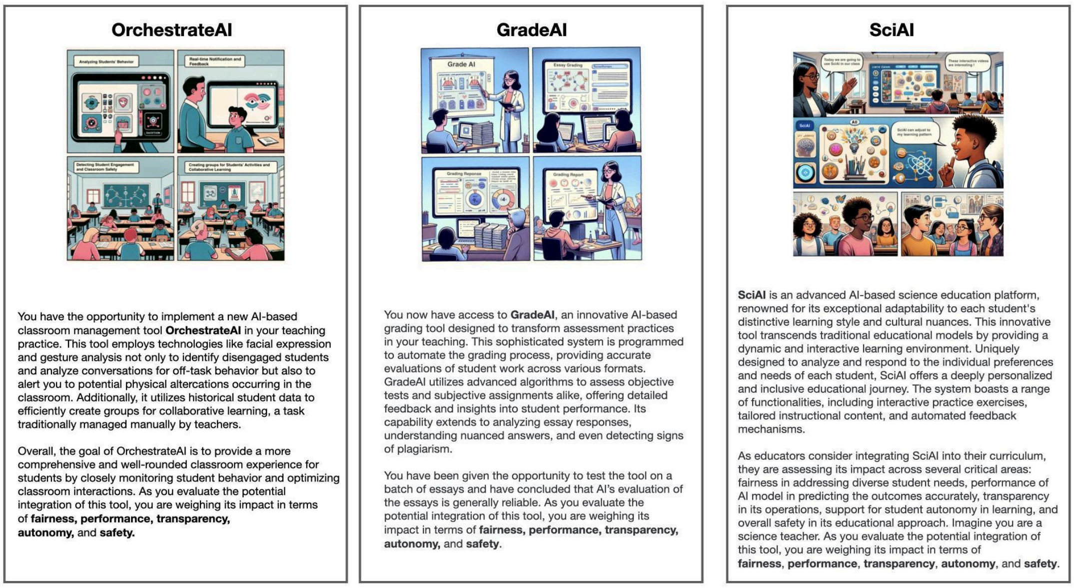


Figure 2

The Introductions of Three AI Scenarios Used in Survey. OrchestrateAI (left), GradeAI (middle), SciAI (right).



Data collection and distribution

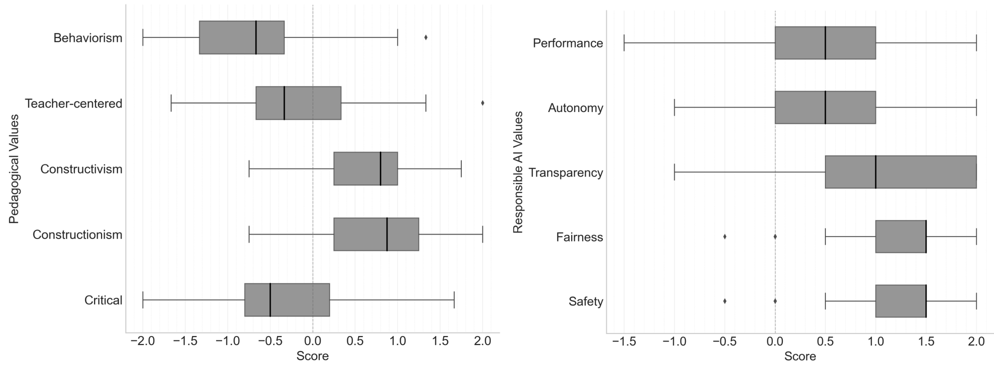
Recruitment and compensation

The research was conducted at a university in the Midwestern United States. To ensure the integrity and reliability of our survey responses, we recruited K-12 teachers (N=98) from internal lists and collaborated with K-12 institutions through the School of Education. As compensation, valid respondents were entered into a raffle for a chance to win one of ten $50 Amazon gift cards.

Data processing and curation

To enable quantitative analysis, participants' responses were transformed into numeric values. For all Likert-scale questions regarding RAI values, we standardized the conversion scale: "Very important" was assigned a value of 2, "Very unimportant" was assigned -2, and intermediate responses were scaled proportionally between these extremes. This approach captured a spectrum of attitudes, ranging from strongly positive to strongly negative. A similar principle was applied to action-oriented questions, where a scoring system ranked participants' selected options from highest to lowest priority. For questions assessing pedagogical values, the ranking of values in a given context determined the score, with values ranging from 2 (highly prioritized) to -2 (deprioritized). Average scores were then calculated as needed, resulting in final value scores ranging between -2 and 2. This standardized scoring system allowed for the comparison and aggregation of responses across participants and scenarios, providing a nuanced understanding of teachers' priorities and decision-making in alignment with the research objectives. The distributions of RAI and pedagogical value scores are illustrated in Figure 3.

Figure 3
Distribution of Scores of Pedagogical Values and Responsible AI Values



Distribution of teachers' demographics, expertise and their classroom compositions

After a three-month data collection period, we obtained a total of 98 valid responses from K-12 teachers. The demographic distribution of participants is presented in Table 1. It's important to note that teachers' demographics were inherently skewed towards certain categories. To examine how the relationship between Pedagogical Values and RAI Values varies by contextual factors in analysis we show later, we focused on variables that were both representative of the sample and non-multicollinear (VIF < 4). These variables included teaching experience, self-rated AI experience, grade level, and classroom composition. By adopting this approach, we aimed to mitigate the effects of demographic skewness while ensuring that key factors influencing teachers' perspectives on RAI in education were adequately captured.

Table 1
Distribution of Teachers' Demographics, Expertise and Their Classroom Compositions

	Demographics	
Gender	Female	73
	Male	24
	Non-binary/third gender	1
Ethnicity	White/Caucasian	91
	Asian	1

	Native American	1
	Black/African American	1
	White/Caucasian,Black/African	1
	Prefer not to say	1
	Other	1
Political orientation	Liberal	70
	Moderate	11
	Conservative	7
	Prefer not to say	9
	Other	1
	Teaching Expertise	
Grade Level	High School (9-12)	45
	Middle School (6-8)	36
	Elementary (K-5)	16
Subject Matter(s)	English/Language Arts	23
	Math	20
	Social Studies	22
	Science	18
	Foreign Language	6
	Other	9
Years of Teaching Experience	0-2 years	20
	3-5 years	30
	6-10 years	16
	11-15 years	10
	16-20 years	6
	21+ years	14
	Classroom Compositions	
Percentage of Students of Color	25% (Lower Quartile)	4.75%
	50% (Median)	15.00%
	75% (Upper Quartile)	65.50%
Percentage of Student with Disabilities	25% (Lower Quartile)	8.00%
	50% (Median)	15.00%
	75% (Upper Quartile)	23.00%
Percentage of Multilingual Students	25% (Lower Quartile)	2.75%
	50% (Median)	7.50%
	75% (Upper Quartile)	25.00%

Results

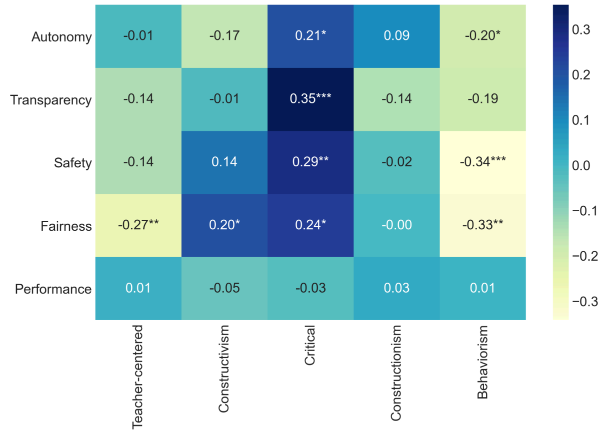
Relationship between pedagogical and responsible AI values

The heatmap in Figure 4 explores how K-12 teachers with varying levels of adherence to different pedagogical values—constructivism, constructionism, teacher-centered approaches, behaviorism, and critical pedagogy—perceive RAI principles. Using Pearson's correlation coefficients, the analysis reveals distinct patterns in how pedagogical values influence the prioritization of RAI values.

Critical pedagogy shows significant positive correlations with transparency ($r = 0.35^{***}$) and safety ($r = 0.29^{**}$), indicating that teachers who emphasize equity and social justice prioritize these values in AI systems. Conversely, teacher-centered approaches and behaviorism display negative correlations with fairness ($r = -0.27^{**}$ and $r = -0.33^{***}$) and safety ($r = -0.34^{***}$ for behaviorism), suggesting that directive, control-oriented teaching styles may conflict with principles emphasizing equity and student well-being. Constructivism and constructionism positively correlate with autonomy ($r = 0.21^{*}$), highlighting that student-centered, active learning pedagogies align with a preference for AI systems that empower student agency and independence.

Figure 4

Correlation Heatmap with Significance between Scores of Responsible AI Values and Pedagogical Values



Note: *, **, and *** indicate significance at $p < 0.05$, $p < 0.01$, and $p < 0.001$, respectively). The x-axis represents pedagogical values, while the y-axis represents Responsible AI (RAI) values.

Our findings highlight the nuanced ways in which teachers' pedagogical commitments shape their perceptions of RAI principles. Teachers aligned with critical pedagogy, constructivism, and constructionism emphasize transparency, safety, and autonomy, while teacher-centered and Behaviorist approaches show weaker alignment with fairness and safety, highlighting potential challenges in integrating AI systems across diverse pedagogical frameworks.

Examining the impact of AI deployment Scenarios, pedagogical values, and classroom factors on teachers' prioritization of Responsible AI values in education

To better understand how AI deployment scenarios, pedagogical values, and classroom factors shape teachers' perceptions of RAI values, we constructed five separate regression models. Each model examined one RAI value—autonomy, transparency, safety, fairness, or performance—as the dependent variable.

Table 2

Regression Summary Table

	Autonomy	Transparency	Safety	Fairness	Performance
Scenario[GradeAI]	0.519	**1.362****	0.315	0.543	-0.081
Scenario[OrchestrateAI]	0.634	**0.885***	0.461	0.726	-0.0083
Scenario[SciAI]	0.585	**0.839***	0.188	0.666	0.283
Teacher-centered	-0.004	-0.135	0.108	-0.283	-0.150
Constructivism	-0.214	-0.090	0.210	0.223	-0.213
Critical	-0.041	0.021	0.264	-0.125	-0.244
Constructionism	-0.021	-0.197	0.089	-0.241	-0.210
Behaviorism	-0.173	-0.199	-0.127	-0.301	-0.063
Pct Students of Color	-0.151	-0.160	0.191	0.304	-0.307
Pct Students with Disabilities	0.010	-0.321	0.131	0.016	-0.050
Pct Multilingual Students	-0.241	0.256	0.437	-0.239	-0.200
Experience Level	0.018	-0.028	0.077	-0.029	0.114
Teaching Experience	-0.006	**-0.080***	0.033	-0.012	0.087
Grade Level	0.005	**0.173***	0.050	0.157	0.056

As shown in Table 2, our findings reveal that transparency is significantly influenced by AI deployment scenarios. Among the scenarios, GradeAI demonstrates the strongest positive effect (1.362**), followed by OrchestrateAI (0.885*) and SciAI (0.839*). Additionally, Teaching Experience shows a small but significant negative relationship with transparency (-0.080*), while Grade Level exhibits a positive relationship (0.173*). These results suggest that the context provided by AI deployment scenarios meaningfully impacts perceptions of transparency. Moreover, teaching experience and grade level also play important roles, indicating that these demographic and contextual factors are associated with how teachers prioritize transparency as an RAI value.

Building on these regression findings, we further explored the distribution of RAI scores across different AI deployment scenarios, teaching experience levels, and grade levels to provide a more nuanced understanding of these relationships. First, as shown in Figure 4, transparency varies significantly across scenarios, with GradeAI showing consistently higher scores, supporting the regression finding that GradeAI has the strongest positive effect on transparency. Other values, such as performance, exhibit less variation across scenarios, suggesting that certain RAI values are less scenario-dependent. Similarly, as shown in Figure 5, transparency scores tend to decrease slightly as teaching experience increases, aligning with the regression model's finding of a small but significant negative relationship. In contrast, values like safety and fairness show stability across experience levels, while performance slightly increases with more experienced teachers. Finally, the grade-level distribution, as illustrated in Figure 6, shows that transparency scores are notably higher for middle and high school teachers compared to elementary school teachers, reinforcing the positive relationship between grade level and transparency identified in the regression analysis.

Figure 4
Distribution of Responsible AI Scores by AI Deployment Scenarios

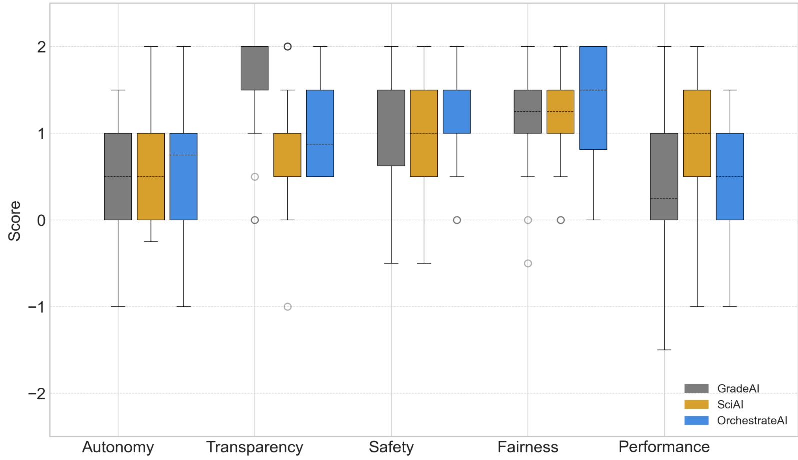


Figure 5
Distribution of Responsible AI Scores by Teaching Experience

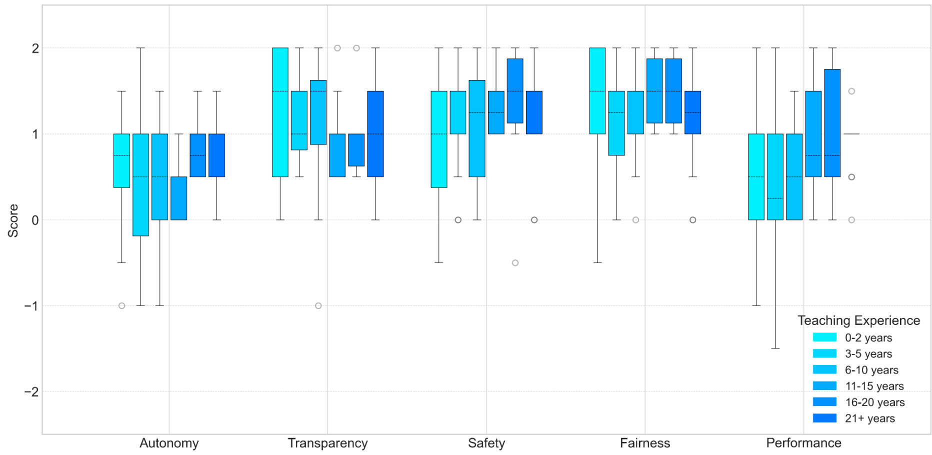
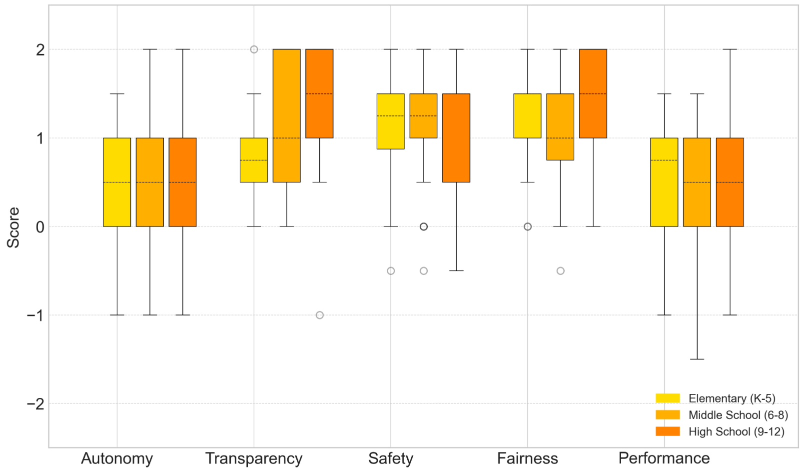


Figure 6
Distribution of Responsible AI Scores by Grade Level



Discussion and conclusion

This study highlights the nuanced ways in which teachers' pedagogical values influence their perceptions of responsible AI (RAI) principles, alongside the role of classroom contexts and AI deployment scenarios. The analysis of RAI scores and pedagogical values reveals distinct alignments and between teaching philosophies and RAI principles. Teachers with critical pedagogy and constructivist values show stronger alignment with RAI principles such as transparency, safety, and autonomy, reflecting their commitment to equity, ethical responsibility, and student-centered practices. In contrast, teacher-centered and behaviorism approaches demonstrate weaker alignment with fairness and safety, indicating potential tensions between directive, reinforcement-based teaching methods and principles that prioritize equity and well-being. These findings underscore the need for AI systems to be designed with flexibility to accommodate diverse teaching philosophies, ensuring successful adoption and alignment with educational goals.

In addition to pedagogical values, AI deployment scenarios and teacher characteristics further shape teachers' RAI priorities. Our results reveal that scenarios significantly influence perceptions of transparency, with GradeAI having the strongest positive impact, followed by OrchestrateAI and SciAI. Similarly, transparency scores are influenced by teaching experience and grade level. Transparency decreases slightly as teaching experience increases, suggesting that more experienced teachers may place less emphasis on this value. Meanwhile, middle and high school teachers prioritize transparency more than elementary school teachers, reflecting heightened concerns about clear and ethical AI practices in more complex educational settings.

These findings have important implications for the development of AI systems in education. AI tools must account for the diversity of pedagogical values and classroom contexts to ensure effective integration. For instance, systems targeting grading or classroom management should prioritize transparency to meet the needs of teachers in these scenarios. Additionally, professional development initiatives should help educators understand how AI systems can align with their pedagogical values, addressing any perceived misalignments and building trust.

In conclusion, this study highlights the complex interplay between pedagogical values, teacher characteristics, and AI deployment scenarios in shaping perceptions of RAI principles. By designing adaptable and equitable AI systems that address these diverse factors, we can better support teachers in fostering effective, inclusive, and student-centered learning environments.

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