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The B-AIMT: development and initial validation of a domain-specific instrument for assessing mathematics teachers' beliefs about artificial intelligence

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This study presents the development of the Belief Scale for Artificial Intelligence in Mathematics Teaching (B-AIMT) and provides psychometric evidence for its initial validation as a domain-specific instrument assessing teachers' beliefs about AI in mathematics instruction. Based on data from 442 German pre-service and in-service teachers, confirmatory factor analyses provided support for a theoretically grounded multidimensional belief structure comprising nine latent belief dimensions organized within two overarching domains: beliefs about student mathematics learning with AI and beliefs about mathematics teaching with AI. The resulting subdimensions capture perceived instructional affordances, epistemic potentials, perceived risks, and ethical considerations related to AI systems. The final measurement model showed satisfactory model fit and good internal consistency. Measurement invariance analyses supported scalar invariance across pre-service and in-service teachers, allowing meaningful comparisons of latent means. These comparisons revealed generally moderate differences, with pre-service teachers reporting higher latent means on several opportunity- and risk-oriented belief dimensions. Overall, the findings suggest that teachers' AI-related beliefs form a differentiated yet coherent belief system characterized by a balanced consideration of opportunities and risks. The B-AIMT provides a theoretically grounded instrument that can support research as well as the design and evaluation of AI-related teacher education and professional development in mathematics.

KEYWORDS
artificial intelligence, beliefs, in-service teachers, mathematics education, pre-service teachers

1 Introduction

The growing prevalence of artificial intelligence (AI) in education, particularly in mathematics education, presents unique opportunities and challenges for mathematics teachers (Fock and Siller, 2025; Hwang, 2023; Pepin et al., 2025; Pörn et al., 2024; Shin, 2020; 2022). As AI-based tools increasingly influence teaching practices, learning environments and curricular structures, (future) mathematics teachers are required to develop competencies that enable them to critically engage with these technologies. Preparing teachers for this emerging technological landscape requires not only technological knowledge but also an understanding of their beliefs about both the potentials and the risks associated with AI in mathematics education. Since beliefs are assumed to significantly influence adoption of innovations and pedagogical decision-making, suitable instruments are needed to capture these beliefs in a valid and systematic way, particularly in the context of teacher education and professional development.

In recent years, several instruments have been developed to assess AI literacy in the general population (Laupichler et al., 2023; Schepman and Rodway, 2020; Sindermann et al., 2021; Wang and Wang, 2019). AI literacy is commonly understood as a set of competencies enabling individuals to critically evaluate, collaborate with, and effectively use AI technologies (Knoth et al., 2024; Long and Magerko, 2020). For example, Laupichler et al. (2023) introduced the SNAIL scale, which measures technical understanding, critical reflection, and application of AI among non-experts. Similarly, Wang et al. (2022) proposed an instrument that assesses AI awareness, usage, evaluation, and ethical considerations. In addition, several scales have been created to measure affective aspects of AI literacy, such as attitudes and emotions, including the ATAI Scale (Sindermann et al., 2021), the General Attitudes Towards Artificial Intelligence Scale (Schepman and Rodway, 2020), and the AI Anxiety Scale (Wang and Wang, 2019).

While these instruments provide valuable insights into general AI literacy, they largely neglect the domain-specific beliefs that shape teachers' readiness to integrate AI into teaching practice. Most existing scales, including those reviewed by Laupichler et al. (2022), focus predominantly on general competencies rather than the pedagogical and disciplinary contexts in which AI is used. Although some studies have begun to address teachers' perspectives (e.g., Ayanwale et al., 2022; Cojean et al., 2023), instruments specifically designed for mathematics education remain scarce.

This gap is particularly relevant because mathematics education presents specific epistemic and pedagogical characteristics. The nature of mathematical reasoning and the emphasis on mathematical precision, formal correctness and conceptual clarity may amplify teachers' concerns about the applicability and educational value of AI tools, particularly given their potential for generating imprecise or erroneous outputs (Buchholtz et al., 2024; Pepin et al., 2025). Even in studies that consider subject specificity, however, the development of reliable and valid instruments for assessing mathematics pre-service teachers' AI-related beliefs remains methodologically challenging (Hwang, 2023; Li, 2024; Pörn et al., 2024).

Moreover, AI literacy itself represents a multifaceted construct that integrates technical knowledge, ethical reflection, and pedagogical application (Knoth et al., 2024; Ng et al., 2021). These dimensions interact in complex ways and require context-sensitive approaches to measurement. In mathematics education, this complexity is further amplified by the need to align AI-related competencies with the epistemic norms and instructional goals of the discipline. Developing instruments that capture these belief structures is therefore essential. Such instruments can support the evaluation of teacher education initiatives, inform professional development programs, and enable comparisons between different groups of teachers, such as pre-service and in-service teachers. Ensuring that these instruments adhere to psychometric standards is imperative, with particular emphasis on thoroughly testing their reliability and validity.

Against this background, the present study aims to develop a domain-specific instrument for assessing mathematics teachers' beliefs about artificial intelligence in mathematics education and to provide psychometric evidence for its initial validation with regard to factorial structure, reliability, and validity. Specifically, we introduce the Belief Scale for AI in Mathematics Teaching (B-AIMT), which captures both cognitive and affective dimensions of AI-related beliefs. Building on recent research on the assessment of AI-related mathematics teacher beliefs (Buchholtz and Schorcht, 2025; Hwang, 2023; Noster et al., 2025) and a theory-informed synthesis of the emerging literature on AI in mathematics education (Buchholtz, 2026), the instrument was designed to reflect theoretically derived dimensions of teachers' beliefs about AI-supported mathematics teaching and learning. Its items therefore address epistemic and pedagogical issues that are particularly salient in mathematics, including conceptual understanding, mathematical reasoning, the evaluation of solution processes, the reliability of AI-generated mathematical outputs, potential de-skilling, and changes in assessment and instructional interaction.

The novelty of the B-AIMT lies in its specific construct focus, target population and disciplinary grounding. Our study makes three main contributions. First, it presents the development of the B-AIMT as a domain-specific instrument for measuring mathematics teachers' beliefs about AI in the teaching and learning of mathematics. Unlike existing AI literacy scales, which primarily assess knowledge, skills, awareness, or general capacities to interact with AI, the B-AIMT focuses on teachers' beliefs as cognitive-affective interpretative frameworks that shape how AI is evaluated in instructional contexts. It also differs from general attitude, anxiety, and technology-acceptance measures by distinguishing multiple belief dimensions rather than locating respondents on a predominantly positive–negative continuum. Second, the study empirically examines the psychometric properties of the instrument using a theoretically grounded confirmatory factor analytic approach to evaluate its reliability and validity. The scale development followed established recommendations (Hinkin, 1998; Worthington and Whittaker, 2006), the development process combined exploratory item refinement procedures with subsequent confirmatory factor analytic evaluation. Third, the study investigates potential differences between pre-service and in-service mathematics teachers with respect to their beliefs about AI in mathematics education.

The remainder of the paper is structured as follows. Section 2 presents the theoretical background and outlines the role of beliefs in teachers' AI literacy. In addition, the section synthesizes prior research on AI-related teacher beliefs in mathematics education and derives the conceptual dimensions underlying the B-AIMT instrument. Section 3 describes the development of the B-AIMT instrument and the methodological procedures used for its initial validation. Section 4 reports the results of the factor analyses and group comparisons. Finally, Section 5 discusses the initial evidence for validity, applicability, and limitations of the proposed instrument, as well as its potential for guiding future research and teacher education initiatives in the area of AI-integrated mathematics education.

2 Theoretical background

2.1 Beliefs of mathematics teachers

Research in mathematics education has consistently demonstrated that teachers' professional actions are shaped not only by their knowledge and skills but also by deeply held beliefs about mathematics, teaching and learning (Liljedahl and Oesterle, 2020; Philipp, 2007). Over the past decades, the study of teacher beliefs has developed into a major research strand within mathematics education, although the construct itself remains conceptually heterogeneous and lacks a universally accepted definition (Cross, 2009; Fives and Buehl, 2012; Liljedahl and Oesterle, 2020; Philipp, 2007). Beliefs are commonly described as psychologically held understandings or premises that individuals regard as true (Richardson, 1996) and that guide their interpretation of situations and actions. Within mathematics education, beliefs have been conceptualized as implicit assumptions that influence how teachers perceive mathematical activity, interpret students' thinking and organize instructional practices (Thompson, 1992). Philipp (2007) metaphorically describes beliefs as "the lenses through which one looks when interpreting the world" (p. 258). This view aligns with Pajares' (1992) argument that all teachers develop beliefs about their roles, students, subject matter and instructional responsibilities. These beliefs operate as interpretative frameworks that structure professional decision-making in classroom contexts (Buchholtz et al., 2023). From the perspective of the affective domain, beliefs are closely related to, but distinct from, attitudes and emotions. Philipp (2007) conceptualizes all three as components of affect that differ in their degree of cognitive structure, stability, and intensity. While attitudes represent more evaluative orientations toward an object and are typically more dynamic, beliefs tend to be more cognitive, relatively more stable, and more closely linked to interpretation and action.

A central feature of beliefs is their organization within broader belief systems. Green (1971) proposed that beliefs are not isolated cognitive elements but rather form structured "belief systems" with varying degrees of centrality. Some beliefs occupy core positions and are highly resistant to change, whereas others remain more peripheral, fluid and flexible. Within mathematics education, such systems shape teachers' broader conceptions of mathematics as a discipline, mathematics teaching and mathematics learning. For instance, Ernest's (1989) influential typology distinguishes instrumentalist, Platonist and problem-solving orientations toward mathematics, each associated with different instructional approaches and expectations regarding students' mathematical activity. Within empirical research, these belief systems are often operationalized as multidimensional latent constructs that capture distinct but interrelated orientations toward mathematics, teaching, learning, and educational innovation.

Beliefs therefore function as cognitive-affective interpretative filters, influencing how teachers perceive and interpret classroom interactions, as well as their willingness to integrate innovative teaching methods, such as using AI tools, into their practices. Research further highlights that within individual belief systems, different and even contradicting beliefs can coexist (Buchholtz and Vollstedt, 2024; Furinghetti and Pehkonen, 2002; Leder et al., 2002; Philipp, 2007). This coexistence reflects the complex and context-dependent nature of teachers' professional thinking. Beliefs are therefore not static entities but evolve through experience, reflection, and professional learning processes. At the same time, the coexistence of contradictory beliefs suggests that teachers' professional belief systems are internally differentiated rather than unidimensional, particularly in contexts of educational innovation and technological change.

Nevertheless, the relationship between teachers' beliefs and their classroom practice is neither linear nor straightforward (Buchholtz and Vollstedt, 2024). Teachers may hold progressive pedagogical beliefs yet fail to implement corresponding practices due to contextual constraints, limited experience, or low confidence in using technology. Teacher education therefore plays a critical role in shaping beliefs. Teacher education and professional development programs that combine theoretical reflection with practical classroom experience provide opportunities for teachers to critically examine their beliefs. However, belief change tends to be gradual and requires sustained engagement and critical reflection over time (Beijaard and De Vries, 1997; De Vries et al., 2013). Factors such as mentorship, classroom experiences and exposure to diverse pedagogical approaches can facilitate this transformation (Van Zoest et al., 1994), but the extent and nature of belief change vary widely among individuals (Erens and Eichler, 2015; Swars et al., 2008).

Beyond mathematics education, the role of beliefs has also been emphasized in established models of technology adoption and integration. The Technology Acceptance Model (TAM; Davis, 1986) explains technology use primarily through perceived usefulness and perceived ease of use, whereas the Theory of Planned Behavior (TPB; Ajzen, 1991) additionally considers subjective norms and perceived behavioral control as determinants of behavioral intention. Both frameworks as well as their theoretical further developments assume that beliefs constitute an important foundation for teachers' decisions to adopt educational technologies. However, these models primarily conceptualize beliefs as evaluations of technology acceptance rather than as broader pedagogical and epistemic belief systems. In mathematics education, teachers' beliefs about AI extend beyond questions of usefulness and usability and include beliefs about mathematical reasoning, conceptual

understanding, assessment, ethical responsibility, and the professional role of teachers.

2.2 AI-related beliefs in mathematics education

Building on these general perspectives on teachers' beliefs and technology adoption, recent research has increasingly examined teachers' beliefs about AI and its role in mathematics education. In mathematics education in particular, teachers' beliefs toward digital tools have been identified as a key factor influencing whether and how technologies are integrated into classroom practice. Studies consistently show that teachers who perceive digital tools as pedagogically valuable and manageable are more likely to incorporate them into their instruction (Erens and Eichler, 2015; Thurm, 2018; Thurm and Barzel, 2020, 2022). Conversely, skepticism and uncertainty regarding technological benefits can hinder adoption, even when adequate technical infrastructure is available.

With the rapid development of AI, this line of research has expanded toward understanding teachers' beliefs about AI-based tools and their potential role in mathematics education (Buchholtz, 2026; Buchholtz and Schorcht, 2025; Busuttil and Calleja, 2025; Noster et al., 2025). AI technologies, particularly generative AI systems and intelligent tutoring systems, introduce new possibilities for supporting mathematical learning, assessment (e.g., Luzano, 2024; Noster et al., 2024) and instructional planning (Buchholtz and Huget, 2024). At the same time, they raise pedagogical, ethical, and epistemological questions that extend beyond those associated with earlier educational technologies (Pepin et al., 2025). Consequently, teachers' beliefs about AI are increasingly recognized as a critical component of their professional readiness to engage with AI-supported learning environments. The emerging research suggests that these beliefs form a multidimensional structure that reflects different pedagogical expectations, professional concerns and ethical considerations. A recent review by Buchholtz (2026) in mathematics education identifies several recurring belief dimensions that shape teachers' evaluations of AI and their readiness to engage with AI-supported teaching and learning environments. Building on this review, the present study conceptualizes AI-related beliefs in mathematics education as a multidimensional and internally differentiated belief system. Across the reviewed literature, recurring dimensions of beliefs about student learning of mathematics with AI consistently relate to perceived support for mathematical understanding and the general learning of skills needed in mathematics instruction, motivational and epistemic affordances of AI, and concerns about de-skilling and consequences for instructional quality. On the other hand, Buchholtz (2026) identified recurring dimensions of beliefs about mathematics teaching with AI, including beliefs about instructional support and differentiation, consequences for the assessment of mathematical achievement, the professional role of teachers and curricular change, as well as ethical concerns and trust in AI systems. These recurring dimensions provide the conceptual framework for the development of the B-AIMT instrument and informed the theoretically grounded specification of the subsequent measurement models.

One central belief dimension of the beliefs about student learning of mathematics with AI concerns the perceived epistemic and conceptual support of AI for mathematical understanding and learning processes. Teachers may believe that AI systems can scaffold students' conceptual understanding, support problem-solving processes, visualize mathematical content, or provide adaptive feedback tailored to individual learning needs (e.g., Albalawi, 2025; Hwang, 2023 Kim, 2024;; Zhao et al., 2025). Closely related to this dimension is the belief that AI may foster broader (cross-domain) competences such as critical or higher-order thinking, strategic reasoning, creativity, and metacognitive regulation, particularly when AI tools are used as interactive learning partners, for example when doing homework, rather than merely as automated solution generators (Albalawi, 2025; Alsharidah and Alkramiti, 2024; Pörn et al., 2024). A third important dimension relates to AI's motivational and affective effects on students' learning of mathematics. Teachers believe that AI-supported learning environments may increase students' engagement, curiosity and confidence when dealing with mathematical problems (Albalawi, 2025; Alsharidah and Alkramiti, 2024; Hwang, 2023; Kim, 2024; Pörn et al., 2024; Uyar, 2025). Through adaptive feedback and personalized learning pathways, AI tools may help students experience success in mathematics, which teachers often associate with higher motivation and stronger self-efficacy. In contrast, the literature also identifies risk-oriented belief dimensions concerning students' learning of mathematics that are related to de-skilling, reduced productive struggle, and a decline in instructional quality. Teachers frequently express concerns that extensive use of AI-generated solutions could reduce students' engagement in productive struggle, which is essential for learning mathematics, weaken their reasoning processes or encourage passive consumption of ready-made answers (Magat and Sangalang, 2024; Pörn et al., 2024; Song et al., 2025; Uyar, 2025).

Further recurring dimensions of the beliefs about teaching of mathematics with AI concern instructional support, assessment practices, and the changing professional role of teachers in AI-supported learning environments. Teachers may view AI as a tool that supports instructional activities, for instance by automating routine tasks or providing diagnostic information about student learning (Colen, 2025; Kim, 2024). However, some educators also worry that extensive AI use could alter classroom interaction patterns or shift authority away from teachers toward technological systems (Wang et al., 2025), thereby transforming established teaching roles (which even includes fears that teachers will be replaced by technology) and intensifying existing inequality among students, particularly in under-resourced schools that lack access to advanced technology (Kim, 2024; Luzano, 2024; Song et al., 2025; Wang et al., 2025). Closely connected to these pedagogical considerations are beliefs regarding AI in assessment and evaluation practices (Luzano, 2024). While some teachers recognize the potential of AI-based systems to provide efficient and fair feedback and diagnostic insights into students' learning progress (Alsharidah and Alkramiti, 2024; Zhao et al., 2025), others remain skeptical about the reliability and fairness of possible automated

assessments, particularly in contexts where complex mathematical reasoning must be evaluated (Albalawi, 2025; Hwang, 2023; Kim, 2024). A further dimension of beliefs concerns the perceived practical benefits of AI for supporting teachers' work (or the reduction of workload, respectively). Teachers often associate AI tools with increased efficiency in lesson planning, the generation of instructional materials, or the differentiation of learning activities (Magat and Sangalang, 2024; Pörn et al., 2024; Shin, 2022; Trung et al., 2025; Yanar and Ergene, 2025). In this sense, AI may be perceived as a supportive professional resource that helps teachers manage heterogeneous classrooms and reduce routine workload.

A further dimension concerns teachers' beliefs about the curricular relevance and future role of AI in mathematics education. Teachers may view AI not only as an instructional tool but as a legitimate and increasingly necessary component of the mathematics curriculum itself. This includes the belief that students should develop an understanding of the mathematical foundations of AI in order to participate in a data-driven society (Albalawi, 2025; Hwang, 2023; Kim, 2024). At the same time, such beliefs are often accompanied by concerns that the integration of AI-related content should not come at the expense of core mathematical ideas and conceptual understanding (Pörn et al., 2024).

In addition to pedagogical and practical considerations, teachers' beliefs also encompass ethical concerns related to AI use in mathematics education (Buchholtz, 2026). Data privacy is a prominent ethical concern when integrating AI into mathematics educational settings. AI systems often require extensive data collection, including students' personal information, performance metrics, and behavioral patterns, to function effectively. This data dependency raises questions about how information is stored, processed, and protected. Teachers express apprehensions about potential misuse of sensitive data, such as breaches of confidentiality or unauthorized access by third parties, which could undermine trust in AI systems. Other issues such as algorithmic bias and the transparency of AI systems are also frequently mentioned in the literature (Albalawi, 2025; Luzano, 2024; Tang and Su, 2024). Environmental dimensions of AI ethics are, however, scarcely represented in the literature. For example, the Turkish study by Çalış et al. (2025) reports moderate levels of digital carbon footprint awareness among pre-service teachers, indicating emerging sensitivity to the ecological impacts of digital technologies more broadly. Finally, teachers' beliefs about AI are shaped by perceptions of trustworthiness and transparency of AI systems. Because many AI technologies operate as complex and opaque systems, teachers may question the reliability and explainability of AI-generated outputs (Albalawi, 2025; Tang and Su, 2024; Uyar, 2025). Such concerns are particularly salient in mathematics education, where accuracy and justification play a central epistemic role (Buchholtz et al., 2024; Pörn et al., 2024). Taken together, the literature suggests that teachers' AI-related beliefs are not organized along a simple positive–negative dichotomy but rather form a multidimensional and internally differentiated belief system. The recurring dimensions identified across studies provide a theoretically grounded basis for the development and initial validation of domain-specific measurement models of AI-related beliefs in mathematics education.

2.3 Measuring teachers' beliefs empirically

In empirical educational research, teachers' beliefs are commonly conceptualized as latent constructs that cannot be observed directly but must be inferred through standardized measurement instruments. Accordingly, Likert-scale questionnaires have become a widely established approach for operationalizing teachers' beliefs in mathematics education research (Buchholtz and Vollstedt, 2024). Such instruments typically assess participants' agreement with a set of theoretically grounded statements and allow the identification and validation of underlying belief dimensions using multivariate statistical procedures, most commonly exploratory and confirmatory factor analyses. Large-scale assessments in mathematics education, such as the international comparative study on mathematics teacher competence TEDS-M (Laschke and Blömeke, 2014) and the German COACTIV study (Kunter et al., 2013), have demonstrated the utility of such instruments for capturing mathematics teachers' beliefs in a standardized and comparable manner across large samples. In particular, factor-analytic approaches enable the examination of dimensionality, reliability, and construct validity of theoretically derived belief structures. Following established recommendations for theory-informed scale development and validation (Hinkin, 1998; Worthington and Whittaker, 2006), the present study combines exploratory item refinement procedures with a theoretically grounded confirmatory factor analytic approach to examine the multidimensional structure of AI-related beliefs in mathematics education.

3 Methodology

Building on the theoretical and methodological considerations outlined above, this study aimed to develop and provide an initial psychometric evaluation of a domain-specific instrument to measure pre-service and in-service mathematics teachers' beliefs about artificial intelligence in mathematics teaching and learning. Following established recommendations for theory-informed scale development and validation (Hinkin, 1998; Worthington and Whittaker, 2006), the scale development process combined theoretically derived construct specification, expert-based item refinement, exploratory item refinement and subsequent confirmatory factor analytic evaluation. The overarching aim of the study is therefore to provide a theoretically grounded and empirically robust measurement instrument that can inform both research and teacher education.

3.1 Research questions

To guide the development and initial validation of the B-AIMT scale, three interrelated research questions were formulated:

RQ1: To what extent does the theoretically derived multidimensional structure of AI-related beliefs in mathematics education receive empirical support in the B-AIMT data?

RQ2: To what extent does the B-AIMT demonstrate satisfactory psychometric properties with regard to model fit, internal consistency, and item performance?

RQ3: To what extent do pre-service and in-service mathematics teachers differ in their beliefs towards AI in mathematics teaching and learning?

RQ1 and RQ2 were addressed through a theory-informed scale development procedure that combined exploratory analyses with subsequent confirmatory factor analytic evaluation. Exploratory analyses were used in an initial refinement phase to examine item performance, conceptual alignment, and the plausibility of the theoretically derived subdomains. The refined models were then evaluated using confirmatory factor analysis (CFA). While RQ1 focuses on the empirical support for the theoretically derived multidimensional belief structure, RQ2 concerns the psychometric adequacy of the resulting measurement models, including model fit, internal consistency, and item performance.

Due to the conceptual heterogeneity and size of the initial item pool, the scale development proceeded iteratively. The initial belief items were first organized into theoretically coherent subdomains and explored using a combination of exploratory factor analyses, inter-item correlations, and internal consistency analyses. Based on these results, preliminary confirmatory factor models were estimated to evaluate item performance and refine the instrument. Following this iterative refinement process, the retained items were integrated into a single confirmatory measurement model representing the final multidimensional belief structure. RQ3 was addressed by first establishing measurement invariance across pre-service and in-service teachers using multigroup CFA and subsequently comparing latent means between both groups.

3.2 Instrument development

The development of the B-AIMT was guided by the multidimensional conceptual framework of AI-related beliefs in mathematics education outlined in Section 2.2 and based on the recurring belief dimensions identified in recent literature reviews and empirical studies on AI-related teacher beliefs in mathematics education (e.g., Buchholtz, 2026). The initial item pool with 72 candidate belief items was designed to capture both opportunity-oriented and risk-oriented beliefs regarding AI-supported mathematics teaching and learning. The item pool was subsequently refined and enriched through iterative expert review procedures involving 12 experts from mathematics education, psychology, computer science, and school practice (both primary and secondary level). The expert panel evaluated the items with regard to clarity, relevance, theoretical alignment, and domain specificity and suggested further items where specific gaps were identified. Across several iterative rounds, items were revised, removed, or reformulated to improve content validity and conceptual coherence.

The broader survey instrument finally comprised 87 Likert-type items addressing different dimensions of AI-related beliefs and also further dispositions like AI readiness and AI-related self-efficacy. The present study focuses specifically on the 70 items of the belief-related dimensions in order to develop and initially validate the B-AIMT as a domain-specific instrument for assessing AI-related beliefs in mathematics education. The remaining 17 items related to AI readiness, self-efficacy, and self-reported competencies were not included in the present analyses and will be examined separately in future research.

All items were formulated as declarative statements such as, "Generative AI tools can foster students' creativity in finding their own solution approaches" or "The use of AI technologies in mathematics instruction raises ethical issues in the area of data protection". Additionally, the developed instrument included demographic questions, such as participants' university affiliation and teacher training program. For the preparation of the empirical data collection, an online questionnaire was designed. All items were measured using a five-point Likert scale ranging from strongly disagree (1) to strongly agree (5), with an additional response option (no response, coded as 9). To ensure the quality of responses, the 87 survey items were randomized across participants. The survey took approximately 20–30 min to complete.

3.3 Data collection and sample

Data for this study were collected in summer 2024. The survey targeted both pre-service mathematics teachers enrolled in university teacher education programs and in-service teachers currently working in schools. Participants were recruited through institutional mailing lists at several German universities (University of Hamburg, TUD Dresden University of Technology, Dortmund Technical University, Julius-Maximilian University Würzburg, University of Siegen, Pedagogical University of Ludwigsburg), and professional teacher networks (Regional Mathematics Teachers' Conferences in Lower Saxony). Participation was voluntary and anonymous. Prior to participation, all participants received information about the purpose of the study, data processing, and the voluntary nature of participation and provided informed consent electronically before beginning the survey.

In total, $N = 442$ individuals participated in the study, including $n = 343$ pre-service teachers from six German universities and $n = 99$ in-service teachers. Table 1 provides a breakdown of the sample by group, including average age for each subgroup.

Overall, the sample predominantly consists of pre-service teachers (78%), while in-service teachers represent a smaller comparison group. As expected, the mean age differs substantially between the two groups, with in-service teachers being approximately 20 years older on average than pre-service participants. This difference reflects the distinct professional stages represented in the sample and provides a basis for the group comparisons conducted in RQ3.

TABLE 1 Sample.

Subgroup	*n*	Mean age (years)	SD age
Pre-service teachers	343	22.99	4.67
In-service teachers	99	42.29	8.46
Total	442	27.32	9.87

3.4 Data analysis

The data analysis proceeded in several stages and focused on structural evaluation of the belief-related dimensions of the B-AIMT instrument. All analyses were conducted using SPSS (Version 29), while confirmatory factor analyses (CFA) were performed in Mplus (Version 8.8). Following established recommendations for theory-informed scale development and validation (Hinkin, 1998; Worthington and Whittaker, 2006), the analytical procedure combined exploratory item refinement with subsequent confirmatory factor analytic evaluation. Exploratory factor analyses (EFAs) were conducted on different subsets of the 70 belief-related items to examine the plausibility of the theoretically proposed subdomains. Because the survey instrument comprised a comparatively large and heterogeneous set of belief items, these exploratory analyses served primarily to evaluate the plausibility of the theoretically proposed subdomains rather than to derive the factor structure purely from the data. EFAs were conducted using principal axis factoring with Promax rotation and Kaiser normalization, allowing the exploratory factors to correlate. Given the theory-informed purpose of the exploratory analyses, factor retention was not determined by a single statistical cut-off. Instead, exploratory loading patterns, factor interpretability, cross-loadings, and the coherence of resulting item clusters in relation to the theoretically derived subdomains were considered jointly. In addition, inter-item correlations, cross-loadings, and internal consistency estimates were examined to identify psychometrically weak or conceptually ambiguous items. Based on these analyses, two preliminary CFA models for the two overarching belief domains (1) beliefs about student learning of mathematics with AI and (2) beliefs about mathematics teaching with AI were specified and iteratively refined. During this process, item performance, modification indices, and residual correlations were examined to identify items with weak psychometric properties or insufficient conceptual alignment with the intended belief dimensions. Items with low standardized factor loadings (<.40) were removed iteratively. At each step, statistical evidence was evaluated together with theoretical interpretability to ensure that the retained items adequately represented the intended belief dimensions. Detailed item-level information on deletion and reassignment decisions during the refinement process is provided in Supplementary Appendix 1. Following this refinement process, a final CFA to examine the latent structure of mathematics teachers' beliefs about artificial intelligence was conducted based on the theoretically proposed multidimensional belief structure and using the complete set of the retained 56 items. Because the exploratory item-refinement procedures, preliminary CFA models, and final CFA were conducted using the same sample, the final CFA should not be interpreted as an independent confirmation of the resulting measurement structure. Rather, it provides confirmatory psychometric evidence for the initial validation of the instrument within the scale-development sample. Independent replication is required to establish the stability and generalizability of the final factor structure.

All belief items were treated as ordered categorical indicators. Model estimation was performed using the weighted least squares mean and variance adjusted (WLSMV) estimator, which is recommended for ordinal categorical indicators such as Likert-type items and is based on polychoric correlations. Model evaluation followed established fit criteria: the Comparative Fit Index (CFI) and the Tucker–Lewis Index (TLI) were expected to exceed .90, while the Root Mean Square Error of Approximation (RMSEA) and the Standardized Root Mean Square Residual (SRMR) were expected to remain below .08 (Hu and Bentler, 1999). In addition to global model fit, factor interpretability and internal consistency (Cronbach's α and McDonald's ω) were used to assess the adequacy of the resulting subscales. To further examine discriminant validity among the resulting latent dimensions, confidence intervals of the latent factor correlations were inspected. In addition, theoretically plausible alternative measurement models representing less differentiated or hierarchically organized factor structures were estimated and compared with the proposed measurement model. Because models were estimated using WLSMV, comparisons of nested models were conducted using the Mplus DIFFTEST procedure.

To address RQ3, measurement invariance across pre-service and in-service teachers was first examined by estimating configural, metric, and scalar multigroup CFA models. Model comparisons were evaluated using changes in CFI, RMSEA, and SRMR following the recommendations of Chen (2007). After establishing scalar measurement invariance, group differences were examined by comparing latent means within the multigroup CFA framework. Pre-service teachers served as the reference group, with latent means fixed to zero, whereas latent means for in-service teachers were freely estimated.

4 Results

4.1 Latent structure and psychometric evaluation of the B-AIMT

To address RQ1 and RQ2, the final CFA was estimated using the complete set of retained belief items. Following the iterative item-refinement process, the resulting measurement model comprised nine correlated latent factors representing different dimensions of mathematics teachers' beliefs about AI in mathematics education. While both research questions rely on the same modeling approach, they target different analytical aspects. RQ1 concerns the extent to which the theoretically derived multidimensional belief structure is supported empirically, whereas RQ2 focuses on the psychometric adequacy of the resulting measurement models.

The final measurement model supported a nine-factor structure comprising 56 items. Fourteen items were removed during the iterative refinement process due to insufficient psychometric performance or insufficient conceptual alignment with the intended belief dimensions. Detailed reasons for item deletion and reassignment are documented in Supplementary Appendix 1. The model showed satisfactory overall fit to the data: $\chi^2(1{,}448) = 2{,}554.81$, $p < .001$, RMSEA = .042, 90% CI [.039, .044], CFI = .908, TLI = .903, SRMR = .059. Although the chi-square test was statistically significant, this finding is not uncommon in CFA models, as the χ^2 statistic is highly sensitive

to sample size and model complexity (e.g., Geiser, 2013). Therefore, model evaluation was based primarily on a combination of global fit indices rather than on the χ^2 statistic alone. Overall, the model demonstrated acceptable fit, with favorable RMSEA (.042) and SRMR (.059) values, while CFI (.908) and TLI (.903) indicated more modest incremental fit. All items loaded significantly on their respective latent factors ($p < .001$), with standardized loadings ranging from .41 to .89. Internal consistency was acceptable to good across subscales, supporting the reliability of the measurement model.

Four of the nine factors reflect distinct dimensions of beliefs about student learning of mathematics with AI (see Supplementary Appendix 2): The first factor reflects beliefs about students' conceptual and process-oriented mathematical learning with AI and beliefs about AI as a general mathematics learning support tool for students (*learn_math_AI*). It comprises 14 items (Cronbach's $\alpha = .86$; McDonald's $\omega = .86$) reflecting teachers' beliefs about AI's contribution to the general comprehension of mathematics in various situations of mathematics instruction. The second factor describes beliefs about the motivational and affective benefits of AI in learning mathematics (*motivation_AI*) in 3 items (Cronbach's $\alpha = .75$; McDonald's $\omega = .78$). The third factor represents beliefs about perceived degradation of students' mathematical competencies through AI use (*deskilling_AI*) and consists of 6 items (Cronbach's $\alpha = .83$; McDonald's $\omega = .83$). The fourth factor refers to beliefs about perceived deterioration of instructional quality through AI (*instr_quality_AI*) and consists of 4 items that describe concerns including dehumanization or diminished interaction in the mathematics classroom (Cronbach's $\alpha = .75$; McDonald's $\omega = .78$).

The model additionally comprises five theoretically interpretable and empirically distinguishable belief dimensions concerning the broader role of AI in mathematics teaching and the professional role of mathematics teachers (see Supplementary Appendix 2). The fifth factor represents beliefs about perceived instructional support and the potential of AI for diagnosing students' learning and the differentiation of instruction (*instr_support_AI*) and consists of 6 items (Cronbach's $\alpha = .86$; McDonald's $\omega = .85$). The sixth factor consists of another 5 items and comprises beliefs about perceived fairness, ethics and equity of AI-based assessment (*assessment_AI*) (Cronbach's $\alpha = .70$; McDonald's $\omega = .70$). The seventh factor consists of 5 items and refers to beliefs about perceived curricular relevance and future importance of AI in mathematics education (*curriculum_AI*) (Cronbach's $\alpha = .73$; McDonald's $\omega = .75$). The eighth factor consists of 6 items and reflects beliefs about perceived impact of the emergence of AI on teachers' professional role and status (*teacher_role_AI*) (Cronbach's $\alpha = .88$; McDonald's $\omega = .88$). Finally, the ninth factor comprises 7 items reflecting beliefs about ethical concerns related to AI use in mathematics teaching, including data privacy, responsible AI use, and the mathematical trustworthiness of AI-generated outputs (*ethics_trust_AI*) (Cronbach's $\alpha = .81$; McDonald's $\omega = .81$).

The latent factors showed moderate to high intercorrelations, indicating that the resulting dimensions form a coherent but internally differentiated belief system rather than fully independent constructs. The pattern of factor correlations suggests a multidimensional structure in which opportunity-oriented belief dimensions (e.g., beliefs about AI-supported mathematical learning, student motivation, instructional support, assessment and curricular relevance of AI) are positively interrelated, whereas risk-oriented dimensions (e.g., beliefs about deskilling, deterioration of instructional quality, ethical concerns related to AI use, and changes in the professional role of teachers) cluster together and tend to show systematic negative associations with opportunity-oriented beliefs (see Table 2). Most interestingly, although both the *assessment_AI* and *ethics_trust_AI* dimensions contain normative considerations and are relatively broad constructs, they differ in their primary referent, which is also consistent with their negative latent correlation. The *assessment_AI* dimension captures potential-oriented beliefs about the appropriateness, fairness, and utility of AI specifically within assessment and performance-monitoring practices (Luzano, 2024). In contrast, *ethics_trust_AI* captures broader concerns regarding the responsible and trustworthy use of AI systems in general, including data protection, algorithmic bias, transparency, and the reliability of AI-generated mathematical outputs (Buchholtz, 2026).

To further examine discriminant validity, the 95% confidence intervals of the latent factor correlations were inspected. Although several correlations were relatively high, none of the confidence intervals included unity. The highest correlation was observed between *deskilling_AI* and *instr_quality_AI* (r = .80, 95% CI [.75, .84]). Similarly, the comparatively high correlations among opportunity-oriented dimensions remained clearly below unity. In addition, theoretically plausible alternative measurement models were compared with the correlated nine-factor model. Combining *deskilling_AI* and *instr_quality_AI* into a single factor resulted in significantly poorer model fit, DIFFTEST $\chi^2(8) = 81.50$, $p < .001$. A higher-order model representing broader opportunity- and risk-oriented belief factors also showed significantly poorer fit, DIFFTEST $\chi^2(26) = 171.88$, $p < .001$. Taken together, these findings provide additional evidence for the discriminant validity of the nine-factor structure, while the observed correlation pattern nevertheless suggests a broader opportunity–risk organization of the specific belief dimensions.

Supplementary Appendix 2 presents the standardized factor loadings from the confirmatory factor analysis (CFA) of the B-AIMT instrument, as well as the means and standard deviations of the items for the overall sample and the individual subgroups. Items are grouped by their respective subscales, which represent different dimensions of beliefs related to AI in mathematics education.

4.2 Differences between subgroups

To address RQ3, latent mean differences between pre-service and in-service teachers were examined within the multigroup CFA framework. Prior to comparing pre-service and in-service teachers, measurement invariance of the final nine-factor B-AIMT model was established. Configural, metric, and scalar invariance models were estimated. The configural model showed satisfactory fit, $\chi^2(2{,}896) = 3{,}786.06$, $p < .001$, RMSEA = .037, 90% CI [.034, .041], CFI = .925, TLI = .921, SRMR = .073, indicating

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TABLE 2 Intercorrelations between dimensions of the final B-AIMT model.

	Learn_math_AI	Motivation_AI	Deskilling_AI	Instr_quality_AI	Instr_support_AI	Assessment_AI	Curriculum_AI	Teacher_role_AI	Ethics_trust_AI
Learn_math_AI									
motivation_AI	.72*								
Deskilling_AI	−.48*	−.35*							
Instr_quality_AI	−.37*	−.32*	.80*						
Instr_support_AI	.71*	.59*	−.34*	−.24*					
Assessment_AI	.72*	.55*	−.38*	−.23*	.69*				
Curriculum_AI	.68*	.51*	−.45*	−.44*	.57*	.55*			
Teacher_role_AI	−.37*	−.28*	.61*	.70*	−.37*	−.41*	−.34*		
Ethics_trust_AI	−.41*	−.33*	.43*	.44*	−.37*	−.41*	−.34*	.26*	

Asterisks indicate statistical significance at $p < .001$.

that the nine-factor structure was acceptable in both groups. Constraining factor loadings to equality across groups did not reduce model fit (metric model: $\chi^2(2{,}943) = 3{,}812.25$, $p < .001$, RMSEA = .037, 90% CI [.033, .040], CFI = .927, TLI = .924, SRMR = .073; ΔCFI = + .002, ΔRMSEA = .000, ΔSRMR = .000). Additional equality constraints on item thresholds also resulted in no meaningful deterioration of model fit (scalar model: $\chi^2(3{,}091) = 3{,}967.35$, $p < .001$, RMSEA = .036, 90% CI [.032, .039], CFI = .927, TLI = .927, SRMR = .074; ΔCFI = .000, ΔRMSEA = −.001, ΔSRMR = + .001). Following conventional criteria for changes in approximate fit indices (Chen, 2007), scalar measurement invariance was supported. Consequently, latent mean differences between pre-service and in-service teachers can be interpreted as reflecting substantive differences in the underlying belief dimensions rather than differences in measurement functioning.

Latent mean comparisons revealed significant differences between pre-service and in-service teachers for several belief dimensions (see Table 3). Relative to pre-service teachers (reference group), in-service teachers reported significantly lower latent means for beliefs about AI-supported mathematical learning (*learn_math_AI*; $\Delta = -0.44$, $p = .001$), perceived risks of deskilling (*deskilling_AI*; $\Delta = -0.45$, $p = .001$), perceived deterioration of instructional quality (*instr_quality_AI*; $\Delta = -0.46$, $p = .001$), beliefs about AI-based assessment (*assessment_AI*; $\Delta = -0.28$, $p = .042$), and beliefs concerning the impact of AI on teachers' professional role (*teacher_role_AI*; $\Delta = -0.51$, $p < .001$). No statistically significant group differences were found for motivational beliefs (*motivation_AI*), instructional support (*instr_support_AI*), curricular relevance (*curriculum_AI*), or ethical and trust-related beliefs (*ethics_trust_AI*).

To provide additional descriptive context for the latent mean differences, exploratory item-level patterns were examined (see Supplementary Appendix 2). These observations are intended solely to illustrate the factor-level results and should not be interpreted as confirmatory findings. The higher latent mean of pre-service teachers in the domain of AI-supported mathematical understanding and learning (*learn_math_AI*) is reflected in comparatively stronger agreement with items referring to epistemic uses of AI, such as supporting the structuring of complex content, facilitating task comprehension, and enabling the analysis of solution processes (e.g., Items 3, 13, 15). A complementary pattern emerges for beliefs on AI's instructional support (*instr_support_AI*), where no significant latent mean difference was found. Item-level inspection suggests somewhat different emphases: while in-service teachers show comparatively stronger agreement with adaptive and diagnostic uses of AI (e.g., differentiation and identification of learners' strengths and weaknesses, Items 36 and 44), pre-service teachers tend to emphasize the potential of AI to reduce teachers' workload (e.g., Items 38 and 39). Similarly, the higher latent means of pre-service teachers in the belief dimensions of *deskilling_AI*, *instr_quality_AI*, and *teacher_role_AI* were reflected in stronger agreement with items addressing potential negative consequences of AI use, including reduced students' self-confidence (Item 28), decreased interpersonal interaction (Items 26–27), and challenges to the professional role of teachers (Item 54). A comparable pattern can be observed for the belief dimension of AI-based assessment (*assessment_AI*).

TABLE 3 Standardized latent mean differences between pre-service and in-service teachers.

Subscale	STDYX latent mean difference (IST vs. PST)	S.E.	*p*	Interpretation
Learn_math_AI	−0.442	0.137	.001 (*)	IST < PST
Motivation_AI	−0.181	0.126	.153	n.s.
Deskilling_AI	−0.452	0.140	.001 (*)	IST < PST
Instr_quality_AI	−0.463	0.138	.001 (*)	IST < PST
Instr_support_AI	−0.023	0.130	.860	n.s.
Assessment_AI	−0.275	0.135	.042 (*)	IST < PST
Curriculum_AI	−0.061	0.134	.649	n.s.
Teacher_role_AI	−0.511	0.130	<.001 (*)	IST < PST
Ethics_trust_AI	−0.103	0.128	.422	n.s.

PST (pre-service teachers) served as the reference group (latent mean = 0). Negative standardized latent means indicate lower latent means for in-service teachers (IST) relative to pre-service teachers. Estimates are based on the scalar invariant multigroup CFA model (STDYX solution).

Pre-service teachers also showed somewhat higher agreement with items referring to the potential of AI to improve fairness and quality of assessment (e.g., reducing subjective bias and enabling continuous performance tracking; Items 40 and 41). At the same time, overall agreement levels in this dimension remained comparatively low across both groups, suggesting a generally cautious stance toward the use of AI in assessment contexts. In contrast, the absence of significant latent mean differences in domains such as *motivation_AI*, *curriculum_AI*, and *ethics_trust_AI* is also mirrored at the item level, where both groups showed largely comparable response patterns.

5 Discussion

The present study developed the B-AIMT instrument and provided psychometric evidence for its initial validation as a domain-specific instrument for capturing pre-service and in-service teachers' beliefs about AI in mathematics teaching. Taken together, the findings provide initial empirical support for a theoretically derived multidimensional belief structure integrating perceived pedagogical affordances, epistemic opportunities, professional implications, and ethical concerns related to AI in mathematics education. This configuration is consistent with prior work on teachers' technology-related beliefs (e.g., Choi et al., 2023; Thurm and Barzel, 2020), yet extends it by embedding these dimensions within the specific epistemic and instructional demands of mathematics education (Fock and Siller, 2025; Pepin et al., 2025). In this sense, the B-AIMT operationalizes AI-related beliefs not merely as general, but as discipline-sensitive belief systems.

From a theoretical perspective, the results can be interpreted through the lens of belief systems (Green, 1971; Philipp, 2007). The factor structure suggests that mathematics teachers' AI-related beliefs are not isolated evaluations but organized configurations that combine perceived potentials with risks and constraints and normative considerations (e.g., ethics, professional role). At the same time, the breadth of the *ethics_trust_AI* dimension indicates that ethical concerns and epistemic trust are closely intertwined in teachers' evaluations of AI. The subscale should therefore be interpreted as a broader ethical-trust dimension rather than as a narrowly defined ethics construct. Notably, the coexistence of positive beliefs (e.g., conceptual support) and critical beliefs (e.g., deskilling, instructional quality risks) within the same respondents reflects the well-documented internal heterogeneity and partial inconsistency of belief systems in mathematics education (Fives and Buehl, 2012; Philipp, 2007). Rather than indicating instability, this pattern points to a differentiated cognitive-affective orientation in which teachers weigh competing considerations when evaluating AI tools and outputs with respect to their daily work (see also Buchholtz and Vollstedt, 2024). At the same time, strong associations between different opportunity-oriented dimensions suggest that some theoretically distinguishable beliefs may be experienced by teachers as part of a more general positive orientation toward AI-supported learning.

With respect to subgroup differences, the latent mean comparisons revealed a consistent pattern in which pre-service teachers exhibited higher latent means than in-service teachers across several belief dimensions, including both opportunity-oriented beliefs (e.g., AI-supported mathematical learning and AI-based assessment) and risk-oriented beliefs (e.g., deskilling, instructional quality, and teachers' professional role). Although statistically significant, these differences were generally moderate in magnitude and should therefore be interpreted with caution. One possible explanation for this pattern relates to the different stages of professional development represented by the two groups. Pre-service teachers, who are still in the process of developing their professional identity, may articulate beliefs about AI in a more idealized and less practice-constrained manner, resulting in stronger endorsement of both perceived opportunities and potential risks. In-service teachers, by contrast, may evaluate AI more strongly in relation to accumulated classroom experience, teaching practices, and the practical constraints of everyday teaching. At the same time, these differences should not be interpreted solely as an effect of professional status. Because the two groups also differed substantially in age, professional experience, and recruitment context, the observed differences may equally reflect these associated characteristics. For example, younger pre-service teachers may be more familiar with recent developments in generative AI through their university studies and broader

public discourse, whereas experienced teachers may evaluate AI more strongly against established instructional practices. Future research should therefore investigate the relative contributions of professional status, age, teaching experience, AI experience, and other contextual variables using multivariate designs. Despite these differences, both groups exhibited broadly comparable overall belief profiles, suggesting that AI is generally perceived neither as an unequivocal opportunity nor as a fundamental threat, but rather as a complex educational technology associated with both considerable potential and important limitations. Exploratory item-level analyses further suggest that the observed differences are primarily reflected in beliefs concerning AI's epistemic support for mathematical learning as well as perceived risks for instructional processes and teachers' professional roles.

Several limitations of the present study should be considered when interpreting the findings. First, the exploratory item refinement and the confirmatory factor analyses were conducted using the same sample. Although the development of the B-AIMT followed a theory-informed procedure and item selection was guided by both statistical evidence and theoretical considerations, using the same participants for model refinement and confirmation may have resulted in somewhat optimistic estimates of model fit and parameter stability. The present findings should therefore be regarded as psychometric evidence for the initial validation of the instrument rather than as an independent validation. Replication of the nine-factor structure and its parameter estimates in an independent sample is required before stronger claims regarding the stability and generalizability of the B-AIMT can be made.

Second, the study focused exclusively on the belief-related dimensions of the B-AIMT. Other components of the broader instrument, such as AI self-efficacy and AI readiness, were not included in the present analyses and should be examined in future validation studies to provide a more comprehensive picture of mathematics teachers' AI-related competencies.

Third, although scalar measurement invariance supported meaningful comparisons between pre-service and in-service teachers, the subgroup analyses should nevertheless be interpreted with caution. The study relied on a convenience sample that was substantially larger for pre-service than for in-service teachers. Moreover, the two groups differed not only in professional status but also in age, professional experience, and recruitment context. Consequently, the observed latent mean differences cannot be attributed exclusively to professional status but may also reflect these associated characteristics.

Fourth, the B-AIMT was developed and initially validated exclusively with German pre-service and in-service mathematics teachers. While the proposed factor structure and psychometric properties were supported within this educational context, their generalizability to other countries and educational systems remains to be established. Given that AI integration in schools is influenced by national curricula, educational policies, and cultural contexts, future research should validate the instrument using independent, balanced and cross-cultural samples before it is applied for broader diagnostic or evaluative purposes.

Finally, as with all self-report instruments, the findings may be affected by response tendencies and socially desirable responding. Although the multidimensional structure of the B-AIMT provides a differentiated assessment of teachers' beliefs, future research should complement questionnaire data with qualitative approaches and classroom-based observations to examine how these beliefs relate to teachers' actual instructional decisions and AI use in practice.

Despite these limitations, the B-AIMT represents a promising, theoretically grounded instrument for research on mathematics teachers' AI-related beliefs and provides a basis for further psychometric validation. In teacher education, it enables the diagnostic assessment of teachers' AI-related belief profiles, allowing teacher education programs to identify specific areas in which future or practicing teachers may require support. For example, the differentiated subscales can help identify whether teachers' reservations primarily concern issues of assessment, instructional quality, ethical considerations, or the perceived impact of AI on students' mathematical learning. Such information may support the design of targeted learning opportunities that not only foster AI-related competencies but also promote critical reflection on the pedagogical and epistemic implications of AI in mathematics education.

Beyond teacher education, the B-AIMT may also support curriculum development by providing empirical evidence on how teachers perceive the role of AI within mathematics teaching and learning. As AI-related competencies become increasingly integrated into national and regional curricula, understanding teachers' beliefs may help identify potential barriers and opportunities for successful implementation. Likewise, the instrument may inform educational policy by providing a means of monitoring teachers' readiness for AI integration and evaluating the impact of large-scale professional development initiatives or policy measures aimed at promoting the responsible use of AI in schools. This is particularly relevant given the widespread assumption that changes in teachers' beliefs are closely related to changes in instructional practice.

From a research perspective, the B-AIMT provides a foundation for investigating how AI-related beliefs are associated with instructional practices, technology use, and student learning outcomes. Longitudinal studies could examine how these belief dimensions develop over time and how they respond to teacher education or professional development interventions. Furthermore, combining the B-AIMT with complementary qualitative approaches may provide deeper insights into how teachers interpret and negotiate the opportunities and challenges of AI in specific instructional situations (see Buchholtz and Vollstedt, 2024). Finally, future research should examine the cross-cultural validity of the instrument and its adaptation to other school subjects, thereby contributing to a broader understanding of AI-related belief systems in education.

Data availability statement

The datasets presented in this article are not readily available because the dataset combines contributions from multiple participating institutions and recruitment contexts. The participating sites agreed to provide data exclusively for the purposes of the present study and did not consent to unrestricted secondary use or public sharing of the complete dataset. As a result, the full dataset cannot be made openly

available. Access to selected parts of the data may be considered on a case-by-case basis and only insofar as this is compatible with the agreements and permissions granted by the participating institutions. Requests to access the datasets should be directed to Nils.Buchholtz@uni-hamburg.de.

Ethics statement

Ethical approval was not required for the studies involving humans because all data used in this study were collected anonymously. No names or other direct personal identifiers were collected, and the data used for analysis did not allow individual participants to be identified. The study consisted of a non-interventional, minimal-risk educational survey of pre-service and in-service teachers. It did not involve vulnerable groups, deception, physical or psychological interventions or burdens beyond those encountered in everyday life, or other particular risks to participants. In accordance with the subject-specific guidance of the German Research Foundation (DFG) for social science and educational research and the applicable institutional requirements, formal ethical review and approval were not required for this study. All participants received information about the purpose of the study, data processing, and the voluntary nature of participation. The studies were conducted in accordance with the local legislation and institutional requirements. The participants provided their written informed consent to participate in this study.

Author contributions

NB: Writing – original draft, Writing – review & editing. SSc: Writing – original draft, Writing – review & editing. KB: Writing – review & editing. LB: Writing – review & editing. NK: Writing – review & editing. ML: Writing – review & editing. D-KM: Writing – review & editing. MM: Writing – review & editing. NN: Writing – review & editing. FP: Writing – review & editing. MP: Writing – review & editing. H-SS: Writing – review & editing. SSp: Writing – review & editing. MV: Writing – review & editing. JW: Writing – review & editing.

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Supplementary material

The Supplementary Material for this article can be found online at: https://www.frontiersin.org/articles/10.3389/feduc.2026.1885959/full#supplementary-material

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