Computers & Education 235 (2025) 105346

Contents lists available at ScienceDirect

Computers & Education

journal homepage: www.elsevier.com/locate/compedu

Development and validation of moral ascendancy and dependency in AI integration (MAD-AI) scale for teachers

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ARTICLE INFO

Keywords:
Moral ascendancy
Dependency
Scale development
Validation
Artificial intelligence

ABSTRACT

Integrating artificial intelligence into teaching practices has become a prominent topic in recent literature, raising concerns about how teachers' moral ascendancy and dependency can be attributed and measured in a behavioral context. This study addresses this gap by developing and validating the teachers' perceived moral ascendancy and dependency on the AI integration (MAD-AI) scale. The methodological process involved the following key steps: initially identifying the scale's dimensionality and creating draft items through a literature review; conducting validation with four experts; revising items based on expert feedback; holding two focus group discussions with six preservice and four in-service teachers; refining dimensions and items based on these discussions; and finally, establishing the psychometric properties of the scale through exploratory factor analysis and confirmatory factor analysis with 383 survey responses from 224 in-service and 159 preservice teachers in the Philippines. The final 30-item MAD-AI scale for teachers includes two dimensions for moral ascendancy: (a) ethical transparency and accountability (7 items) and (b) professional integrity (8 items), as well as two dimensions for dependency: (a) institutional support (8 items) and (b) educator preparedness (7 items). Results demonstrated acceptable fit measures, strong reliability, convergent validity, and discriminant validity, supporting the structural soundness of the scale.

1. Introduction

1.1. Background and gap

Artificial Intelligence (AI) mimics human intelligence, which introduces novel structures, teaching methods, and personalized educational experiences that were previously unavailable (Lameras & Arnab, 2021). The rapid advancement of AI has impacted various aspects of human life, raising ethical and moral concerns about its adoption. For instance, what moral foundations can we theorize to determine whether the use of AI and AI systems in a particular workplace is morally upright? This question has been a point of investigation among scholars, especially given that individuals from different backgrounds may hold diverse moral foundations

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https://doi.org/10.1016/j.compedu.2025.105346
Received 9 February 2025; Received in revised form 2 May 2025; Accepted 3 May 2025
Available online 6 May 2025

(Harper & Rhodes, 2021; Telkamp & Anderson, 2022). The moral considerations influencing AI usage cover various dimensions, including perceptions and practical factors, and are particularly prominent among the digital native population. In line with having the authority or ascendancy to utilize AI, how do we measure the behavior associated with its use? Also, how do we measure the dependency on AI? These questions will be linked to a behavioral evaluation to ensure controlled acceptance of AI, preserving moral agency (Clark & Gevorkyan, 2020). The key focus is assessing individuals' moral ascendancy and dependency as they integrate AI into their daily lives. This study aimed to develop a tool to measure teachers' perceived moral ascendancy and dependency regarding integrating AI and AI systems in educational settings.

The development of a scale for teachers stems from the need to assess moral ascendancy and dependency on AI integration, particularly within the educational system. Although AI advancements show great potential for aiding educational purposes, they should be seen as a partial solution, as their successful implementation in education requires ongoing attention and research. As AI develops, educators are at the forefront of this technological shift, with educational leaders increasingly incorporating AI systems in their institutions (Chiu & Chai, 2020). Therefore, AI has the potential to enhance teaching and learning significantly, but its widespread adoption is not guaranteed. This uncertainty stems from the possibility that teachers might need more knowledge, training, and institutional support, hindering their ability to effectively integrate AI into their teaching practices (Mercader & Gairín, 2020).

Additionally, concerns about teachers' moral authority in using AI tools raise ethical issues and potential misuse, which could lead to a lack of transparency and accountability and diminish the human element in education (Robinson, 2020). While current research on scale development (SD) addresses the integration of AI in education, emphasizing ethical considerations, more research is needed to explore teachers' moral authority in applying AI in educational contexts. The ethical dimensions and dependencies involved in teachers' use of AI have yet to be thoroughly investigated. Further arguments are presented as we explore the dimensions of moral ascendancy and dependency in the methods section, where part of the approach involves identifying the dimensions of the scale through a conceptual literature review. Although a scale exists to measure university students' dependence on AI based on dimensions such as fear of missing out and validation checking (Morales-García et al., 2024), the behavioral construct of dependency in the context of AI integration among teachers remains unexplored. This study builds its framework through conceptual mapping of existing literature and qualitative validation to establish relevant dimensions of the topic.

This paper aims to develop a scale called the "Moral Ascendancy and Dependency in Artificial Intelligence" (MAD-AI) to measure and assess the dimensions of moral ascendancy and dependency among teachers in integrating AI in their classes. The MAD-AI Scale provides a framework for evaluating teachers' moral ascendancy and dependency, enabling behavioral scientists to explore hypothetical connections with various behavioral concepts and better understand the complexities of AI integration in the education system. This area has not yet been studied in the current literature. The closest established scale is the one developed by Banks (2019), which covers perceived moral agency for human beings and machines such as robots or chatbot assistants. This paper contextualizes how humans perceive morality and the dependency on integrating AI into teaching and learning. Ng et al. (2024) assess AI literacy and include ethical considerations as one of its dimensions, drawing on psychometric properties from student respondents. However, these do not address the moral ascendancy and dependency of teachers. Other relevant scales include the ethical leadership framework focusing on moral management aspects (Zhu et al., 2019), the "Perceived Role of Ethics and Social Responsibility" scale (Singhapakdi et al., 1996), the "Moral Authority Scale" (White, 1996), and the "Ethical Leadership at Work Questionnaire" (Kalshoven et al., 2011). Each of these differs from the current work in terms of behavioral constructs, sources of behavior, contextual influences, and psychometric measurement approaches.

1.2. AI and educational leadership

Artificial intelligence (AI) refers to the simulation of human intelligence in machines that are programmed to process information and respond in ways similar to humans (Dong et al., 2020). AI involves developing methods and algorithms that enable technology to perform tasks that usually require human intelligence (Hassani et al., 2020). It covers a wide range of techniques, such as machine learning, robotics, visual computing, and natural language processing. The purpose of AI is to generate tools with intellectual capabilities that correspond to humans, including the capacity for learning, reasoning, problem-solving, understanding, and communication (Jarrahi, 2018). As AI continues to develop, educational leaders face numerous challenges in integrating it into academic settings, including the behavioral sciences.

The integration of AI in education offers an important change in the modern educational setting, reshaping conventional methods of instruction (Kinshuk et al., 2016). Implementing AI affordances in education is essential as AI is becoming integral to nearly every industry, necessitating a clear connection between education and industry, a trend that continues to evolve. Wang (2021) argued that educational leaders must adopt appropriate approaches to AI integration, fostering symbiotic relationships at the formative stages of learning. This is particularly important given that over a third of jobs are currently at high risk due to automation and AI integration. The management of AI integration is a role among educational leaders in protecting the "humanity paradigm," which is aimed at preserving the future of humanity (and even other living creatures) through the development of social intelligence (Fullan et al., 2024). Thus, it is assumed that teachers should exhibit adaptive leadership when using AI tools. AI can enhance leadership by expanding pedagogical horizons (e.g., automating tasks and personalizing learning platforms) or diminish it when technology takes over key responsibilities (Ghamrawi, Shal, & Ghamrawi, 2024). These key points prompt critical questions: What does the future hold for AI tools in schools? What impact will they have on education stakeholders, particularly teachers and learners? How should moral ascendancy be managed? These arguments underline that ethical considerations are among the primary concerns when managing AI integration in the educational system.

1.3. Moral ascendancy in AI integration

To provide proper context, this subsection connects how morality, ascendancy, and moral ascendancy can steer our discussions on the need to create a moral ascendancy scale for teachers in integrating AI into education. From foundational work, morality refers to principles and standards that help people or society discern between good and evil, as well as acceptable and undesirable behavior, which are collectively called morality (Kant, 2013). It is the result of an interconnectedness of ethical theories, societal expectations, cultural norms, and personal views that shape the context in which people make moral decisions and judgments (Schwartz, 2016). Morality becomes a concern regarding the moral problems surrounding AI development, application, and utilization. Morality in this context includes responsibility, bias, ethical impact, and social influence, which may differ depending on how AI is used in education (Telkamp & Anderson, 2022). The moral side of AI involves how systems are designed and used in ways that responsibly shape students' learning environments (Dodig-Crnkovic, 2012). This aligns with the OECD's call for "responsible stewardship for trustworthy AI," where teachers, as AI facilitators in learning science, are expected to support inclusion, human values, transparency, safety, and accountability (Yeung, 2020).

Ascendancy is a term used to describe a position of dominance, influence, or elevated status in a specific field or organization (McGuire, 1983). In educational settings, ascendancy is a person's perceived superiority or authority, typically observed by teachers over their students or school administrators over their teachers. In AI integration, ascendancy refers to the power or authority that individuals or organizations, such as teachers or school administrators, hold over the direction of AI implementation within educational frameworks, guided by established contextual ethical leadership (Nguyen et al., 2023; Shapiro & Stefkovich, 2016). This idea concerns teachers' power, control, or ethical influence in the application, use, and moral concerns related to AI in educational settings. Teachers' ascendancy is based on their moral leadership in managing the ethical issues and implications of AI integration in classroom settings (Berkovich & Grinshtain, 2023). Ascendancy in educational policy and governance relates to the influence and authority of curriculum developers and educational leaders when choosing the more appropriate integration frameworks and approaches for AI in education (Vinothkumar & Karunamurthy, 2022). For teachers, the ascendancy they uphold must follow the moral standards set in the curriculum and protect the learners' best interests.

Morality, authority, and ethical leadership are interconnected yet distinct concepts that can contribute to the broader idea of moral ascendancy in the context of AI integration in education. Moral ascendancy refers to a teacher's ethical influence and responsibility in guiding AI adoption while maintaining fairness, integrity, and accountability regardless of diverse human moral foundations (Telkamp & Anderson, 2022). While moral authority is the credibility gained through consistent ethical behavior and ethical leadership focuses on setting ethical standards, moral ascendancy emphasizes the teacher's influence. Rooted in classical philosophy, this concept reflects Aristotelian notions of phronesis (practical wisdom), where educators act ethically and cultivate moral character and reasoning in others (Crisp, 2014). Students naturally seek recognition from individuals they perceive as possessing practical wisdom, such as teachers and educational leaders. This is where moral ascendancy comes in—the relational aspect of moral leadership in education that forms part of ethical understanding, particularly in emerging areas like AI integration.

In their role as character builders, teachers form a big chunk of responsibility for the holistic development of the learners and share accountability in shaping the younger generations into distinct, virtuous persons. The Philippines serves as the case point of this study, where teachers are regarded as direction-setters, character builders, and agents of change, covering various moral expectations of their role (de Leon-Carillo, 2007). The concept is not parochial to the case country, as the related moral concepts such as transparency, integrity, and fairness are recognized across global contexts. Literature provided dimensional chunks, including ethical transparency (Bogina et al., 2022; Memarian & Doleck, 2023), accountability (Cheong, 2024; Nguyen et al., 2023), equity and fairness (Kumar & Choudhury, 2023; Yu & Yu, 2023), and professional integrity (Balalle & Pannilage, 2025; Cotton et al., 2024; Striepe et al., 2023). The conceptual literature review is presented in Section 3.1. In this conceptual mapping, the moral ascendancy of teachers is reflected in their capacity to influence others, uphold moral standards, and align teaching practices with ethical values. These roles were theoretically mapped within the evolving context of AI integration in learning environments and platforms.

Incorporating AI platforms into the learning process must be viewed carefully, considering the latest capabilities of an AI tool and how it provides added power to teachers (Holmes & Tuomi, 2022; Lameras & Arnab, 2021). Thus, keeping abreast of technological knowledge is a moral obligation of the teachers since they are at the forefront of ensuring the integrity of its implementation. Professional integrity in the implementation of teaching is viewed as following the morally upright coherence at the crossroads of personal and pedagogical integrity (Finefter-Rosenbluh, 2024). In AI integration, teachers must focus on choosing the right path and maintaining justice and moral reasoning if confronted with ethical dilemmas. In its expanded context, the concept covers equity and fairness, which is argued to be in line with Kohlberg's theory of cognitive ethics, where cognitive morality is keenly considered in AI integration (Kumar & Choudhury, 2023). Given the moral-ecological framework, teachers' ethical deliberations regarding AI also involve navigating complex moral tensions and maintaining trust in AI-enhanced education (Finefter-Rosenbluh, 2024; Serholt et al., 2017). When integrating AI into their teaching practices, teachers perceive ethical leadership, professional integrity, and responsibility as key elements of moral ascendancy. These dimensions are presented in Section 3.1.

1.4. Dependency

Dependency is operationally defined as an individual's reliance on or influence by technology, particularly in AI, which can carry out a variety of tasks that still require assistance from humans to complete them. Building on Banks' (2019) argument that enacting moral functions involves a range of motivations and dynamics influencing human-AI interactions, the definition is framed as a set of factors shaping this reliance. When integrating AI into the teaching process, dependency intersects with two subtopics based on literature: (1) educator preparedness, which includes contextual and meta-contextual intelligence of the teachers (Luckin et al., 2022), and (2) institutional support, which includes providing professional development opportunities and infrastructure (Costan et al., 2021; Khan et al., 2017). Although other specific dimensions—such as technological confidence, ethical awareness, and policy familiarity—could still be explored, they can generally be represented under the broader categories of educator preparedness and institutional support. To avoid underextending and overcomplicating the construct, we acknowledge these subdimensions and recommend their further investigation in future studies.

Educator preparedness may form some necessary conditions for successfully integrating AI into education. Teachers must develop AI literacy and skills to effectively use AI tools in the classroom. For instance, AI can enhance tutoring in higher education, but teachers must be well-prepared to use these technologies to their full potential (Hemachandran et al., 2022). Building on this argument, dependency can be linked to established frameworks such as Technological Pedagogical Content Knowledge (TPACK) (Mishra & Koehler, 2006) and AI literacy models (Long & Magerko, 2020), which cover the role of technological knowledge in effective teaching and creating learner-centered AI tools. Generating items to measure dependency concerning technological knowledge must consider well-established behavioral factors influencing the construct. For instance, content knowledge is essential for effectively applying technological competencies in educational settings (Valle et al., 2024), while pedagogical skills must align with the technological tools a teacher intends to use (Gonzales & Gonzales, 2021). Teacher professional development programs are the bedrock of successful AI literacy implementation, grounded in clear definitions that include ethical considerations (Ding et al., 2024; Ng et al., 2021). Transparent, interpretable, and understandable AI in education allows educators to comprehend how AI tools work and how they can be ethically applied in teaching (Khosravi et al., 2022). The effectiveness of AI tools in education depends on teacher preparedness. Well-trained teachers use these tools more effectively to support student learning.

Institutional support is a dimension of dependency because effective AI integration relies on available resources, clear guidelines, and strong leadership within the educational ecosystem of the school. Ethical leadership contributes to institutional support by shaping

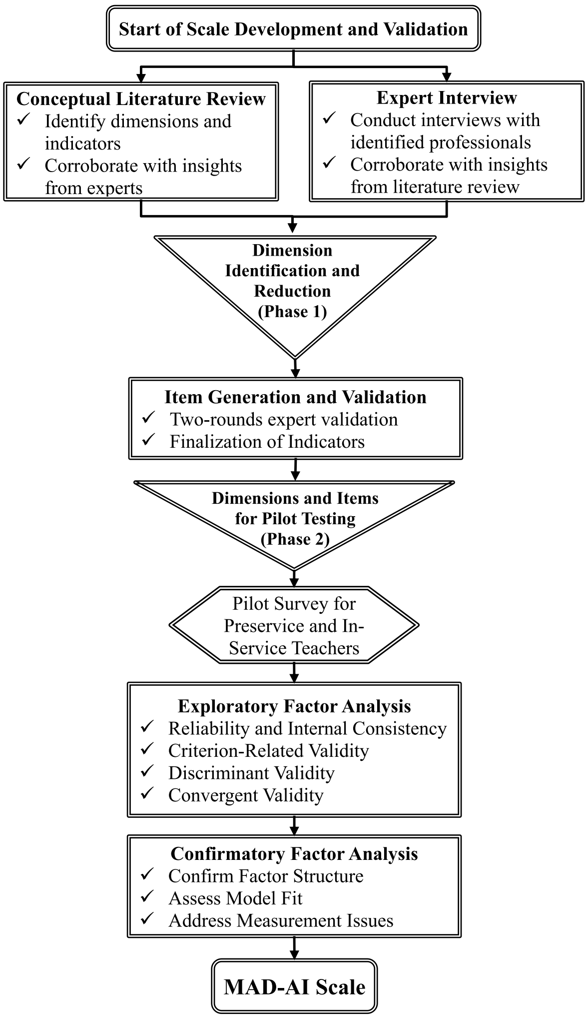

Fig. 1. The process flow chart of MAD-AI scale development.

policies and practices that guide the responsible integration of AI in education (Shapiro & Stefkovich, 2016). Embedding ethical principles into institutional frameworks establishes guidelines for the appropriate and responsible use of AI tools (Nguyen et al., 2023). Educational institutions must provide the necessary infrastructure, resources, and professional development to support educators (Chen et al., 2020; Costan et al., 2021). Institutions must also address both the opportunities and challenges of AI adoption, specifically regarding sustainability and effectiveness in the learning environment (Kuleto et al., 2021). Providing teachers with ongoing support helps them enhance their professional knowledge and enables them to ethically integrate AI tools into their teaching practices (Celik, 2023). Thus, there is a need for a scale to assess institutional support as a dimension of dependency in the integration of AI in education.

2. Methods

2.1. Procedure

Fig. 1 outlines the process flow chart detailing the steps from the initial development to the finalization of the dimensions and indicators for the MAD-AI scale for teachers. The process began with identifying dimensions and creating item indicators through corroborative findings from conceptual literature review and focus group discussions (FGDs), forming Phase 1 of the scale development. Interview transcripts were analyzed using NVivo Pro version 11 software. The coding procedure involved a collaborative process where the authors used NVivo to identify nodes based on word frequency. This was followed by team discussions to agree on codes and themes for collective input. After determining the initial dimensions and items, two rounds of expert validation were conducted to refine and purify them. This step was part of Phase 2, aimed at reducing dimensions and finalizing the item indicators to capture each latent factor more accurately.

A conceptual literature review was conducted to capture and define the dimensions of moral ascendancy and dependency as the key constructs. The methodology allows the researchers to synthesize conceptual definitions, frameworks, and models that understand the factors influencing a concept (Findley, 1989; Solway et al., 2016). The goal was to uncover a conceptual map of the latent constructs of "moral ascendancy" and "dependency," which serve as the basis for developing dimensions and indicators for a measurement tool. The selection criteria for articles were those indexed in reputable scientific databases, specifically from Scopus and Web of Science.

Following the expert validation depicted in Fig. 1, the refined items were pilot-tested to establish the scale's psychometric properties. A survey was conducted, and the responses were analyzed using Exploratory Factor Analysis (EFA) and Confirmatory Factor Analysis (CFA). This analysis assessed the following psychometric properties: (1) reliability and internal consistency, (2) criterion-related validity, (3) discriminant validity, (4) convergent validity, and model fit of latent factor structure. These analyses were performed using IBM SPSS and AMOS 27® software. The final indicators for the MAD-AI scale were established with statistically confirmed reliability, convergent validity, and structural utility.

EFA identifies the underlying data structure and helps uncover the number of factors and the relationships between observed variables and those factors without imposing a specific framework (Fabrigar et al., 1999). It allows researchers to find patterns in data, remove or revise poorly performing items, and ensure that each item contributes meaningfully to the scale (Field, 2013). By conducting EFA first, we gain insights into the data's structure, which helps refine the scale for further validation using CFA. The purpose of CFA is to validate the factor structure of a measurement model, establishing that the observed variables (indicators) accurately reflect the underlying latent constructs (Hair et al., 2010). CFA tests the hypothesized relationships between observed variables and latent factors, enabling researchers to confirm or reject their proposed model. This process involves evaluating the scale's psychometric properties, including reliability, validity, factor loadings, measurement errors, and fit indices, to ensure the model accurately represents the data.

2.2. Participants

The research participants consisted of three distinct groups, each defined by specific inclusion and exclusion criteria and the nature of the data being gathered. The first group included informants from the focus group discussions conducted during Phase 1 of the scale's dimensionality development. This group comprised six preservice teachers participating in FGDs and three in-service teachers who were interviewed individually. The inclusion criteria for preservice teachers required current enrollment in a teacher education program and experience using AI in their classes under the supervision of a professor. In-service teachers were required to have completed a degree in education, be actively teaching, and have applied AI in performing teaching-related tasks. Another inclusion

Table 1
Demographic characteristics of the participants ($n = 383$).

Category		n	%
Sex	Male	75	19.58 %
	Female	308	80.42 %
Age	22 and below	128	33.42 %
	23–27	83	21.67 %
	28–32	66	17.23 %
	33 and above	106	27.68 %
Respondent Type	Preservice teacher	159	41.51 %
	In-service teacher	224	58.49 %

criterion is whether participants have experience using or have been exposed to AI or AI-assisted tools in their teaching or learning practices.

The second group of participants consisted of four expert validators, who were selected based on specific criteria: they must hold the position of associate professor or full professor in a college of teacher education, have publications related to scale development or factor analysis in Scopus-indexed journals, and possess a doctorate in education. The last respondent group comprised individuals who volunteered to participate in the pilot survey, with inclusion criteria limited to preservice and in-service teachers. A total of 383 participated in the survey, whose demographic distribution is presented in Table 1.

2.3. Ethical review clearance

This study received institutional ethics review clearance on April 18, 2024. The research processes and data collection were classified as "exempted" for low risk. The research team remained fully committed to upholding ethical standards throughout the process, including interviews, surveys, data analysis, reporting, and publication, to protect all participants' rights and well-being.

3. Results

The initial step in identifying potential dimensions for the scale involved conducting a conceptual literature review, which was then triangulated with focus group discussions involving six preservice teachers and individual interviews with three in-service teachers. The findings from this process are presented in the following subsections.

3.1. Conceptual literature review

A conceptual literature review synthesizes theoretical and empirical studies to define, refine, and explore key concepts related to a specific topic (Snyder, 2019). In this study, the review captures dimensions of moral ascendancy and teacher dependency relevant to integrating artificial intelligence (AI) in education. The goal was to develop a conceptual mapping, centered on the latent constructs of "moral ascendancy" and "dependency," to inform the dimensions and indicators of a measurement tool. Table 2 presents the list of references, the selection of which is based on their indexing in scientific databases such as Scopus and Web of Science (WOS), as well as the credibility of their publishers.

Table 2
Dimensionality identification through conceptual literature review.

Dimensions/Constructs	Sources	Type	Indexing	Publisher
Moral Ascendancy				
Ethical Transparency	McLennan et al. (2022)	Journal Article	Scopus, WoS- SSCI and SCIE	BMC
	Memarian and Doleck (2023)	Journal Article	Scopus	Elsevier
	Hagendorff (2020)	Journal Article	Scopus, WoS- SSCI	Springer
	Balasubramaniam et al. (2023)	Journal Article	Scopus, WoS-SCIE	Elsevier
	Bogina et al. (2022)	Journal Article	Scopus	Springer
Transparency and Accountability	Stathis and van den Herik (2024)	Journal Article	Other (e.g., ANVUR, Baidu)	Springer
	Mittelstadt et al. (2016)	Journal Article	Scopus, WoS- SSCI	SAGE
	Jobin et al. (2019)	Journal Article	Scopus, WoS-SCIE	Nature
	Cheong (2024)	Journal Article	Scopus, WoS-ESCI	Frontiers
	Nguyen et al. (2023)	Journal Article	Scopus, WoS- SSCI	Springer
Equity and Fairness	Bass and Steidlmeier (1999)	Journal Article	Scopus, WoS-SSCI	Elsevier
	Hagendorff (2020)	Journal Article	Scopus, WoS-SCIE	Taylor & Francis
	Kumar and Choudhury (2023)	Journal Article	Scopus, WoS-SCIE	Elsevier
	Matias and Zipitria (2023)	Conference Paper	Scopus, WoS - SSCI	Springer
	Yu and Yu (2023)	Journal Article	Scopus, WoS-SSCI	Frontiers
Professional Integrity	Finefter-Rosenbluh (2024)	Journal Article	Scopus, WoS- SSCI	Taylor & Francis
	Lynch et al. (2022)	Journal Article	Scopus, WoS- SSCI	Elsevier
	Striepe et al. (2023)	Journal Article	Scopus, WoS- ESCI	Springer
	Cotton et al. (2024)	Journal Article	Scopus, WoS- SSCI	Taylor & Francis
	Yusuf et al. (2024)	Journal Article	Scopus, WoS- SSCI	Springer
	Balalle and Pannilage (2025)	Journal Article	Scopus	Elsevier
Dependency				
Educator Preparedness	Hemachandran et al. (2022)	Journal Article	Scopus	Wiley
	Khosravi et al. (2022)	Journal Article	Scopus	Elsevier
	Luckin et al. (2022)	Journal Article	Scopus, SNIP	Elsevier
	Berkovich and Grinshtain (2023)	Journal Article	Scopus, WoS- ESCI	Taylor & Francis
	Ding et al. (2024)	Journal Article	Scopus, WoS- ESCI	Elsevier
Institutional Support	Shapiro and Stefkovich (2016)	Book	Scopus	Routledge
	Nguyen et al. (2023)	Journal Article	Scopus, WoS- SSCI	Springer
	Khan et al. (2017)	Journal Article	Scopus, WoS- SSCI	Taylor & Francis
	Kuleto et al. (2021)	Journal Article	Scopus, WoS- SSCI and SCIE	MDPI
	Celik (2023)	Journal Article	Scopus, WoS- SSCI	Elsevier

The results of the systematic literature review identified four potential behavioral constructs of *moral ascendancy* and two for *dependency* in the context of technological integration in education, particularly AI. The moral ascendancy covers *ethical transparency*, *accountability, equity, fairness,* and *professional integrity*. Dependency is represented by *educator preparedness* and *institutional* support. From the concepts mapped in Table 2, we theoretically establish the dimensionality of moral ascendancy and dependency on AI integration in the teaching and learning process.

3.2. Qualitative triangulation

The focus group and one-on-one interviews involved six preservice teachers and four in-service teachers who shared their views on AI integration in education. The preservice participants, all specializing in mathematics, were selected because they were the only ones who met the inclusion criteria (as outlined in Section 2.2) during data collection. While their specialization is mathematics, their perspectives are assumed to share the same applications of AI use across different specializations. The in-service teachers represented various fields and had prior experience with AI-assisted teaching. Each interview consisted of six open-ended questions with follow-up probes and lasted between 15 and 28 min.

Participants shared their experiences using AI in teaching and learning, reflecting on the dimensions and possible indicator systems to measure the construct. Their responses present recurring themes, which were analyzed for word frequency using NVivo Pro version 11 software. We employed a framework integrating initial lexical analysis through NVivo's Word Frequency Query with collaborative thematic coding to guide our qualitative analysis. This approach follows Jackson and Bazeley's (2019) recommendation to use word frequency results as an entry point to identify dominant concepts within qualitative data. Frequently occurring terms were used to create preliminary nodes in NVivo, which served as provisional categories for deeper thematic exploration. As a group, we examined the context of these nodes, discussed their conceptual relevance, and refined them into broader themes. This process enabled a structured yet flexible coding workflow, combining data-driven insights with interpretive judgment.

The results consistently aligned with the proposed dimensions, confirming their relevance as latent constructs. Word frequency was categorized into nodes and was linked to the dimensions of moral ascendancy and dependency. We excluded the terms "AI" and "artificial intelligence" in the node identification as these terms are broadly applicable across all dimensions and stemmed from 370 references, the most in number among the frequency counts. These constructs have been captured in the discussions, with the term "AI" consistently emerging as a central theme throughout the interview.

From the identified nodes in the interview transcripts, overlapping themes emerged among the constructs of "ethical transparency" and "transparency and accountability." Although these constructs were initially derived from different sources in the literature (e.g., Hagendorff, 2020; Jobin et al., 2019; Memarian & Doleck, 2023), their underlying discussions converged on similar ideas, which can be collectively generalized as "ethical transparency and accountability." Thus, we find it necessary to reduce constructs under the moral ascendancy dimension from four to three, reflecting a more streamlined framework. Table 3 illustrates this adjustment, with nodes corresponding to each dimension, supported by sources and references from the interview transcripts.

Table 3
Summary of NVivo nodes in the qualitative dimension reduction.

Dimension	Construct	Nodes	Sources	References
Moral Ascendancy	Ethical Transparency and Accountability	Practice/practices	7 (77.78 %)	41
		Access/accessible/accessibility	5 (55.56 %)	26
		Incorporate/incorporating	8 (88.89 %)	44
		Teach/Teaching/Teacher	9 (100 %)	109
		Students/learners	9 (100 %)	115
		Ethics/ethical	4 (44.44 %)	12
	Professional Integrity	Teach/Teaching/Teacher	9 (100 %)	109
		Profession/Professional	7 (77.78 %)	27
		Incorporate/incorporating	8 (88.89 %)	44
		Ethics/ethical	4 (44.44 %)	12
		Integrity	5 (555.56 %)	25
	Equity and Fairness	Incorporate/incorporating	8 (88.89 %)	44
		Use/using/usage	9 (100 %)	113
		Practice/practices	7 (77.78 %)	41
		Ethics/ethical	4 (44.44 %)	12
Dependency	Educator Preparedness	Teach/Teaching/Teacher	9 (100 %)	109
		Students/learners	9 (100 %)	115
		Use/using/usage	9 (100 %)	113
		Practice/practices	7 (77.78 %)	41
		Access/accessible/accessibility	5 (55.56 %)	26
		Understand/understanding	6 (6.67 %)	30
	Institutional Support	Tools	5 (55.56 %)	46
		Use/using/usage	9 (100 %)	113
		Need/needs	4 (44.44 %)	32
		Training	4 (44.44 %)	21
		Teach/Teaching/Teacher	9 (100 %)	109
		Incorporate/incorporating	8 (88.89 %)	44

In Table 3, the "Sources" column indicates the number of informants who referenced specific terms related to the dimension. For instance, the term "practice/practices" was mentioned 41 times by 7 or 77.8 % of the informants during the interviews. The transcripts containing these references were aligned with the dimension of ethical transparency and accountability, particularly in using AI in teaching and learning processes. The conceptual mapping of these terms was grounded theoretically from the literature review, mapping the identified concepts to the established dimensions. The arrangement and identification of relevant nodes were conceptually captured based on the interview transcripts.

The mapping of nodes to constructs was based on carefully analyzing how each term emerged within the context of the participant's responses. The assignment was collaboratively discussed among the authors. Some nodes were found to overlap across constructs, as specific terms reflected elements of more than one construct. For example, one participant mentions adequate preparation and ethical awareness when incorporating AI tools: "*I feel comfortable incorporating AI into my teaching as long as I have proper training, resources, and a clear understanding of the ethical guidelines*" (Participant 6). This quote is drawn from the node "*incorporating*," relating to the constructs of *Professional Integrity*, *Ethical Transparency and Accountability*, and *Equity and Fairness*.

3.3. The final constructs, item generation, and expert validation

Five constructs emerged (see Table 3) from the analysis of interview transcripts, classified into two primary dimensions: (1) the moral ascendancy dimension, encompassing the behavioral constructs of (a) ethical transparency and accountability, (b) professional integrity, and (c) equity and fairness; and (2) the dependency dimension, comprising the behavioral constructs of (a) educator preparedness and (b) institutional support. The subsequent discussions detail the mentions, nodes, and behavioral classifications associated with each construct. Drawing from the literature relevant to the keywords identified in the word cloud analysis, operational definitions for these constructs were established.

Under the *moral ascendancy* dimension, ethical *transparency and accountability* were noted to have seven frequently referenced key nodes, totaling 347 mentions. These terms reflect concepts leading to indicators for this dimension. Operationally, *"ethical transparency and accountability"* are the principles and practices that ensure clarity, honesty, and responsibility in actions, decisions, and the use of technologies, particularly in education and AI. This definition is supported by literature on ethical transparency (e.g., Hagendorff, 2020; Jobin et al., 2019), denoting open communication, fair access to information, and clear articulation. Under the ethical AI framework (Floridi & Cowls, 2022), questions like "How does it work?" and "Who is responsible for the way it works?" guide the standards for transparency and accountability. These core principles help inform the development of indicators for these constructs. For example, teachers are responsible for addressing mistakes when using AI in teaching and ethically giving students clear rules for using AI-generated content.

Professional integrity, on the other hand, is represented by five key nodes, with a total of 217 referenced terms, including "teach/teaching/teacher," "profession/professional," "incorporate/incorporating," "ethics/ethical," and "integrity." Operationally, we define professional integrity as the adherence to ethical standards and practices by educators, ensuring fairness, honesty, and accountability, specifically in the context of AI and education. This definition points out accountability and moral consistency in designing and implementing IT systems in educational settings (Lynch et al., 2022). Another segment of represented sources could be accounted for *equity and fairness,* with 210 mentions from four nodes, including the root terms incorporate, use, practice, and ethics. Equity and fairness refer to just and impartial treatment, providing equal opportunities, and addressing individual needs to achieve balanced outcomes. Designing and implementing AI tools that eliminate bias, promote inclusivity, and consider diverse learner profiles, making sure that every student has access to quality education regardless of their background (Holmes & Tuomi, 2022). The concept aligns with the UNESCO AI Competency Framework for Teachers (AI CFT), emphasizing principles such as an inclusive digital future, lifelong learning for teachers, and a human-centered approach to AI integration (Cukurova & Miao, 2024). These principles provide a framework for the ethical and pedagogical dimensions of using AI in education and support professional growth for teachers anchored from a global perspective.

In the *dependency* dimension, the *educator preparedness* has key nodes including the root words such as "*teach*" (109 references), "*students/learners*" (115 references), "*use*" (113 references), "*practice*" (41 references), "*access*" (26 references), and "*understand*" (30 references) with a total of 434 references. Educator preparedness refers to teachers' readiness, adaptability, and capability to integrate AI tools into their teaching practices effectively. It covers teachers' knowledge, skills, and attitudes toward adopting AI technologies to meet educational goals (Luckin et al., 2022). Another construct in the dependency dimension is *institutional support.* The construct emerged from the key themes reflected in the frequent use of root words such as "*tools*" (46 references), "*use*" (99 references), "*need*" (32 references), "*training*" (21 references) and "*incorporate*" (44 references), with a total of 365 references. Institutional Support refers to the resources, policies, infrastructure, and training an organization provides to facilitate the effective adoption, implementation, and integration of tools, technologies, or practices. In AI and education, institutional support offers educators access to training programs, technological resources, clear guidelines, and ongoing assistance to ensure ethical, efficient, and equitable use of AI tools in teaching and learning environments (Luckin et al., 2022). The AI CFT outlines key competencies for teachers' preparedness to use AI in education. Dependency and the ethical use of AI in education rely on infrastructure, AI resources, data security, policy guidance, and professional development (Cukurova & Miao, 2024). Based on the trustworthiness and moral applicability of AI platforms, scales to assess behavioral factors are indispensable for evaluating AI integration.

The items for the MAD-AI scale were developed based on insights from the literature review (Section 3.1) and qualitative triangulation through expert interviews (Section 3.2). A total of 50 items were created, distributed across the following dimensions: (1) the Moral Ascendancy dimension, which includes (a) Ethical Transparency and Accountability (10 items), (b) Professional Integrity (10 items), and (c) Equity and Fairness (10 items); and (2) the Dependency dimension, comprising (a) Educator Preparedness (10 items) and (b) Institutional Support (10 items). These items underwent two rounds of expert validation. Two experts participated in the validation process, meeting the inclusion criteria of holding advanced degrees in research and evaluation and being recognized scholars in the field. Table 4 summarizes the two-round expert validation of the scale items.

3.4. Establishing the psychometric properties of the scale

Establishing the psychometric properties of the indicators is a critical aspect of scale development. This section outlines the processes undertaken, including pilot testing, detecting potential multicollinearity among constructs, assessing reliability and validity, identifying factors and their loadings, and determining the latent structures of the MAD-AI scale.

3.4.1. Pilot testing

Building on the initial 50-item MAD-AI scale indicators established in subsection 3.3, a pilot test was conducted with 383 teachers, comprising 159 preservice teachers and 224 in-service teachers. The demographic characteristics of the survey participants are detailed in Section 2.2. The primary aim of the survey was to evaluate the scale's psychometric properties and refine the items by assessing the reliability, validity, and model fit through factor analyses.

3.4.2. Multicollinearity and reliability assessment

Table 5 presents the constructs' zero-order correlations, descriptive measures, and Cronbach's alpha. It can be gleaned that all correlations are significant at 0.01 alpha level. High correlations were present, like ETA and EF ($r = .839$), ETA and EP ($r = .765$), and EF and EP ($r = 796$), while others had moderate and low correlations.

Highly correlated constructs generally pose multicollinearity concerns. Although the threshold value for correlations that are considered problematic is above 0.85 (Dormann et al., 2013; Field, 2013), the high correlation between ETA and EF (0.84) may suggest conceptual overlap, which should be considered in the factor analysis. The reliability of all constructs (ranging from 0.930 to 0.979) is excellent, assuring consistency in the measurement scale. However, factor analysis still needs to be examined to confirm dimensionality. In such cases, revisions or removal of redundant items may be necessary.

3.4.3. Exploratory factor analysis

Table 6 presents the final results following a series of exploratory trials conducted in SPSS. The maximum likelihood method was used for factor extraction. Initially, the pattern matrix identified six factors, but after seven exploratory trials, the analysis refined the solution to four factors: Ethical Transparency and Accountability (ETA), Professional Integrity (PI), Educator Preparedness (EP), and Institutional Support (IS). These trials evaluated cross-loadings, weak loadings, and overall model fit to ensure robust factor structure (Hair et al., 2010; Kline, 2011).

The EFA process validated the 35-item MAD-AI scale, removing three items from ETA, the entire EF construct, and two from EP. All items for IS and PI were retained. Interestingly, most EF items displayed cross-loadings across factors 2, 3, 4, 5, and 6 in the initial exploratory pattern matrix, with low factor loadings ranging from 0.307 to 0.761 (values < 0.3 suppressed). This gives us a reason to believe that the results reflect (a) conceptual overlap, (b) weakness in psychometric properties, and (c) theoretical insufficiency of the EF construct. Based on the literature surrounding EF and its relation to the other constructs of moral ascendancy (i.e., ETA and EP), EF is inherently represented in transparency, accountability, and integrity in decision-making (Hagendorff, 2020; Jobin et al., 2019). Also, within EP, EF aligns with equitable teaching practices and fairness in addressing diverse learners' needs (Luckin et al., 2022). These overlapping themes suggest that EF is effectively integrated within ETA and EP, rendering it unnecessary as a separate construct. Consequently, the EF construct was excluded to enhance the model's parsimony and theoretical clarity.

The final EFA model (rotation converged in 5 iterations) is well-supported by significant statistical tests. Bartlett's test of sphericity ($\chi^2 = 16,784.692$; $p < 0.05$) confirms sufficient common variance to justify factor analysis, while the Kaiser-Meyer-Olkin (KMO) measure of sampling adequacy is 0.962, indicating an excellent level of suitability (Kaiser, 1974). Items with eigenvalues below 1.0 were removed, commonalities dropping below 0.20 were flagged for exclusion, and factor loadings for each retained item exceeded the threshold of 0.50. As to criterion-related validity, an evaluation of how accurately the MAD-AI scale measures what it was designed to measure, the total scores of the 35-item scale were simultaneously measured alongside valid criterion scores. The two criterion items achieved a significant coefficient alpha of 0.961. A positive correlation between the total score and the valid criterion indicates an

Table 4
Summary of two-round expert validation on the MAD-AI scale.

Dimension/Construct	Round 1			Round 2		
	Accepted	Rejected	Revise	Accepted	Rejected	Revise
Moral Ascendancy						
Ethical Transparency and Accountability	7	0	3	9	0	1
Professional Integrity	6	0	4	9	0	2
Equity and Fairness	8	0	2	10	0	0
Dependency						
Educator Preparedness	8	0	2	9	0	1
Institutional Support	7	0	3	10	0	0

Table 5
Zero-order correlations, descriptive measures, and Cronbach's alpha of the study variables.

Study Variables	ETA	PI	EF	EP	IS
ETA	1				
PI	0.712[a]	1			
EF	0.839[a]	0.792[a]	1		
EP	0.765[a]	0.720[a]	0.796[a]	1	
IS	0.308[a]	0.472[a]	0.440[a]	0.371[a]	1
Mean	5.889	5.873	5.676	5.621	4.403
Standard Deviation	1.111	1.266	1.212	1.054	1.626
Cronbach Alpha	0.939	0.974	0.948	0.930	0.979

[a] Correlation is significant at the 0.01 level (2-tailed).

Table 6
Summary of EFA result.

Dimension	Construct	Item Code	Factor			
			1	2	3	4
Moral Ascendancy	Ethical Transparency and Accountability (ETA)	ETA01				0.875
		ETA02				0.853
		ETA03				0.891
		ETA04				0.907
		ETA05				0.725
		ETA09				0.565
		ETA10				0.614
	Professional Integrity (PI)	PI01		0.881		
		PI02		0.865		
		PI03		0.793		
		PI04		0.838		
		PI05		0.929		
		PI06		0.916		
		PI07		0.829		
		PI08		0.921		
		PI09		0.926		
		PI10		0.865		
Dependency	Educator Preparedness (EP)	EP01			0.835	
		EP02			0.968	
		EP03			0.875	
		EP04			0.759	
		EP05			0.853	
		EP06			0.502	
		EP07			0.559	
		EP08			0.841	
	Institutional Support (IS)	IS01	0.910			
		IS02	0.904			
		IS03	0.924			
		IS04	0.917			
		IS05	0.933			
		IS06	0.896			
		IS07	0.891			
		IS08	0.930			
		IS09	0.889			
		IS10	0.882			

Table 7
Zero-order correlations, Descriptive Measures, and Cronbach's Alpha of the Study Variables after EFA.

Study Variables	ETA	PI	EP	IS
ETA	1			
PI	0.669[a]	1		
EP	0.730[a]	0.730[a]	1	
IS	0.275[a]	0.472[a]	0.377[a]	1
Mean	6.036	5.873	5.670	4.403
Standard Deviation	1.120	1.266	1.147	1.626
Cronbach Alpha	0.940	0.974	0.953	0.979

[a] Correlation is significant at the 0.01 level (2-tailed).

accurate measurement of the MAD-AI final constructs. The findings suggest a criterion-related validity of 0.864 for the 35-item instrument, with a 0.01 significance level.

Table 7 presents correlations, descriptive statistics, and reliability measures of the items to prepare the validation of the factor structure for CFA. All correlations are positive and significant, ranging from 0.275 to 0.730. With acceptable fit measures and factor loadings in CFA, the relatively high correlations between certain constructs (e.g., EP-ETA, EP-PI) suggest conceptual alignment rather than redundancy, supporting the model's overall structure. In contrast, IS shows weaker correlations with ETA ($r = 0.275$), PI ($r = 0.472$), and EP ($r = 0.377$), indicating that IS operates as a more independent construct. Reliability analysis shows all constructs achieving excellent Cronbach's alpha values (>0.90), confirming internal consistency (Cook & Beckman, 2006). Item-total correlations were computed per construct to support reliability analysis and identify weak items. Following the threshold of ≥0.30 (DeVellis & Thorpe, 2021), all items exceeded this criterion.

However, exceptionally high alpha values for PI ($\alpha = 0.974$) and IS ($\alpha = 0.979$) still indicate potential redundancy among items, warranting closer inspection. For CFA, it is recommended to test the measurement model using fit indices (e.g., CFI, RMSEA) and assess discriminant validity to address possible multicollinearity among the highly correlated constructs. Reviewing the items for IS and PI during CFA may help enhance its distinctiveness, while item reduction techniques could mitigate redundancy, achieving a more parsimonious model (Kline, 2011).

3.4.4. Confirmatory factor analysis

After the EFA results, a confirmatory factor analysis (CFA) was performed using AMOS 27® Software to confirm factor structure. The factor groupings established in EFA were assessed to determine whether these factor structures hold in a separate sample by evaluating model fit, factor loadings, and construct validity (Hair et al., 2019; Kline, 2011). Table 8 presents the goodness-of-fit indices for CFA.

A total of 383 responses were loaded into CFA. The final model fit measures presented in Table 8 were acceptable with ($\chi^2 = 979.136$; $df = 417$; $p < 0.01$; $\chi^2/df = 2.348$, RMSEA = 0.059, CFI = 0.959, and TLI = 0.955). The acceptability of the obtained RMSEA value is supported by Hu and Bentler's (1999) assertion that RMSEA values up to 0.06 indicate a good fit. The SRMR was 0.046, indicating a good model fit (Brown, 2006). These findings validate that the factor structure identified in EFA accurately represents the data, reinforcing the construct validity.

Fig. 2 shows the final number of indicators for the MAD-AI scale after CFA: ETA has seven indicators, PI has eight indicators, EP has eight indicators, and IS has eight indicators, totaling 31 indicators. To address shared method variance (Podsakoff et al., 2003), 11 error covariances with high modification indices were introduced. This adjustment improves model fit while allowing room for further refinement, such as revising item wording, checking for redundancy, or removing potentially overlapping items. Allowing error covariances is acceptable when items share similar wording or content, as it reflects shared measurement variance rather than model misspecification (Byrne, 2013). These modifications were theory-driven and improved model fit without compromising construct validity. We reported key fit indices—CFI, RMSEA, and SRMR—which met the recommended thresholds (see Table 8). This indicates that the model maintained acceptable fit and parsimony despite the added covariances (Byrne, 2013; Hair et al., 2019).

The CFA results in Table 9 indicate strong measurement properties for the constructs. Standardized factor loadings exceed the recommended threshold of 0.7 (Bagozzi & Yi, 1988), ranging from 0.765 to 0.927. The results demonstrate strong relationships between observed variables and their respective latent constructs (Hair et al., 2010). Composite reliability (CR) values for all constructs exceed the 0.7 threshold value (Malhotra, 2010), ranging from 0.939 to 0.972, confirming excellent internal consistency. However, the high CR value for IS (0.972) suggests potential redundancy among its items, warranting further review of indicators to avoid redundant items.

The Average Variance Extracted (AVE) values are all above 0.5, ranging from 0.688 to 0.815. This means that the constructs capture more variance than measurement error, which aligns with the criterion proposed by Fornell and Larcker (1981) for convergent validity. The Cronbach's alpha values range from 0.940 to 0.979, indicating reliability across the constructs for good internal consistency. These results provide strong evidence for the reliability and validity of the measurement model.

3.5. Final item refinement and reduction

The MAD-AI scale items confirmed in EFA and CFA still allow room for refinement due to several key considerations: (a) multiple covariances were applied to improve model fit, (b) the high CR value for IS (0.972), and (c) the high Cronbach's alpha for IS (0.979). While the scale demonstrates acceptable psychometric properties based on model fit measures, potential redundancy within the IS construct should be addressed.

Table 8
Goodness-of-fit indices for CFA.

Type of fit indices	Indices	Sample	Criteria	Sources of Criteria	Evaluation Outcomes
Absolute fit indices	(χ2/df)	2.348	<3	Kline (2011)	Good Fit
	RMSEA	0.059	<0.06	Hu and Bentler (1999)	Good Fit
	SRMR	0.046	≤0.08	Brown (2006)	Good Fit
Incremental fit indices	CFI	0.959	≥0.95	Hu and Bentler (1999)	Good Fit
	TLI	0.955	≥0.95	Brown (2006)	Good Fit

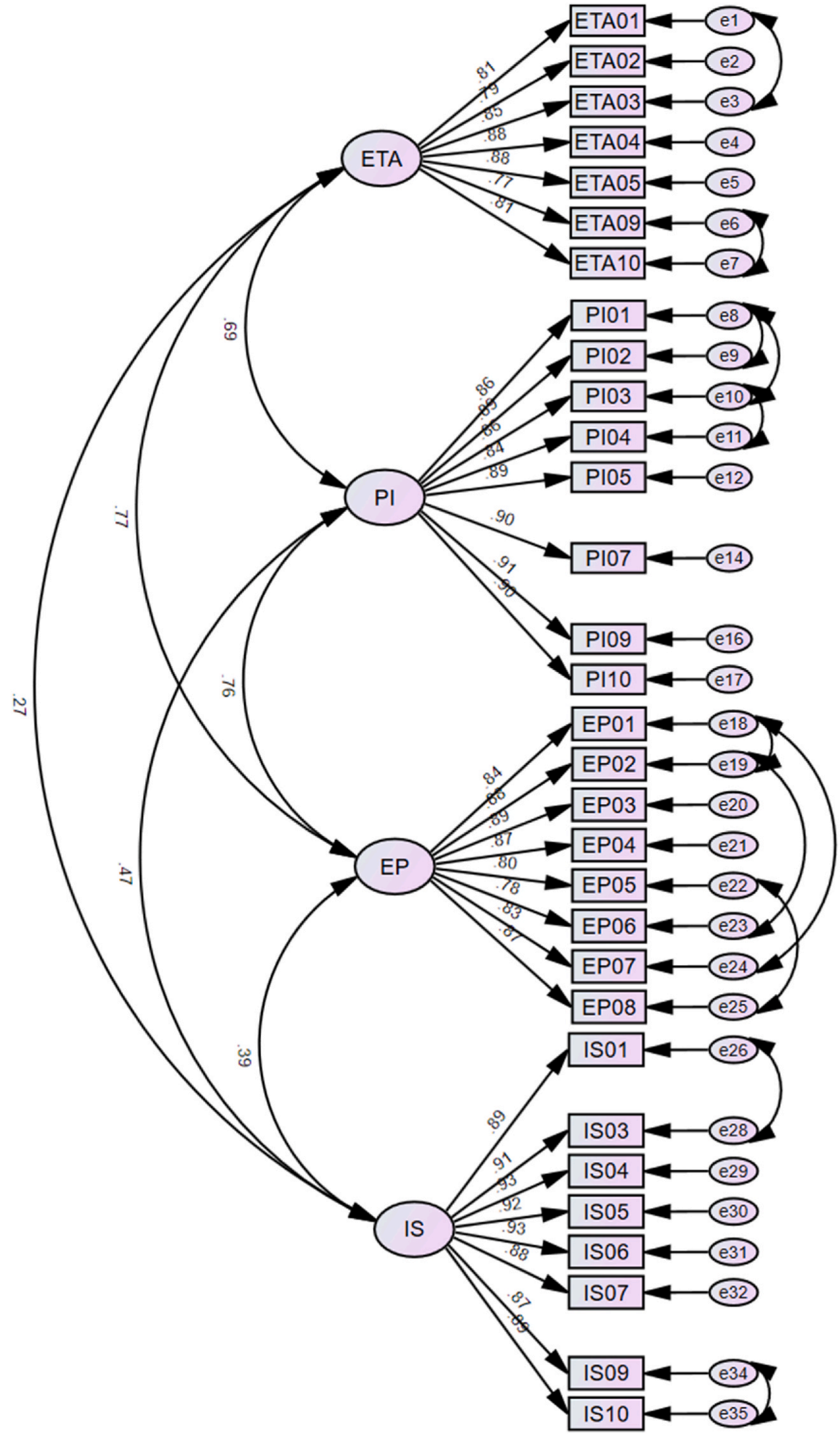

Fig. 2. A factor structure model of the MAD-AI scale.

Upon further analysis, IS09 and IS10 were the first indicators to be covariates in CFA, with a modification index exceeding 50. Given this, we identified IS09 for removal as it had the lowest factor loading (0.868) among IS items. Following this reduction, the final MAD-AI scale now consists of 30 items: ETA with seven indicators, PI with eight indicators, EP with eight indicators, and IS with seven indicators. The final indicators are detailed in Table 10.

Table 9
CFA results of the final measurement model.

Dimension	Construct	Item Code	Standardized Loadings	CR	AVE
Moral Ascendancy	Ethical Transparency and Accountability (ETA)	ETA01	0.809	0.939	0.688
		ETA02	0.786		
		ETA03	0.855		
		ETA04	0.882		
		ETA05	0.881		
		ETA09	0.771		
		ETA10	0.813		
	Professional Integrity (PI)	PI01	0.864	0.965	0.777
		PI02	0.886		
		PI03	0.857		
		PI04	0.837		
		PI05	0.888		
		PI07	0.901		
		PI09	0.914		
		PI10	0.902		
Dependency	Educator Preparedness (EP)	EP01	0.842	0.953	0.719
		EP02	0.884		
		EP03	0.889		
		EP04	0.874		
		EP05	0.804		
		EP06	0.779		
		EP07	0.832		
		EP08	0.874		
	Institutional Support (IS)	IS01	0.887	0.972	0.815
		IS03	0.912		
		IS04	0.927		
		IS05	0.924		
		IS06	0.930		
		IS07	0.883		
		IS09	0.868		
		IS10	0.890		

4. Conclusion

This paper developed and validated a 30-item Moral Ascendancy and Dependency in AI Integration (MAD-AI) scale for teachers through a scientific process involving a conceptual literature review, expert evaluation, and empirical testing to establish its psychometric properties. The scale's validity, reliability, and structural soundness were established through exploratory and confirmatory factor analyses (EFA and CFA) conducted during a pilot survey involving 383 pre-service and in-service teachers in the Philippines. The results showed strong model fit indices and demonstrated utility and convergent and discriminant validity.

The MAD-AI scale development is grounded in the growing need for ethical AI usage in educational settings, addressing concerns raised by the rapid rise of generative AI. The scale aligns with existing literature on teachers' roles as moral leaders. As AI becomes increasingly integrated into education, the MAD-AI scale serves as a framework for educators to establish behavioral structures that address both the ethical challenges and opportunities of AI adoption.

5. Recommendations for future research

This study offers MAD-AI's key behavioral constructs; however, several areas remain open for further exploration. First, future research may investigate more conceptually broad subdimensions that may still be categorically identified. Second, while the current study focused on a first-order factor structure, future studies may explore the potential of second-order or bifactor models, especially in diverse educational settings or with expanded construct sets. Lastly, further validation may be pursued by integrating the developed constructs with external criteria to assess their relevance and alignment within broader structural models.

6. Limitations

Like other scale development studies, this paper acknowledges certain limitations that do not compromise the overall findings or applicability of the results. First, the sample is limited to teachers in the Philippines, which may restrict the generalizability of the scale to other cultural or educational contexts. Second, nomological validity was not assessed, as the study focused on establishing construct validity rather than testing the scale within a broader theoretical framework. Third, while qualitative data informed the initial item pool, future studies may benefit from a more extensive and diverse qualitative base to improve the dimensional coverage of the construct.

Table 10
The 30-item MAD-AI scale.

Moral Ascendancy
Ethical Transparency and Accountability (ETA)
I check the credibility of the AI tools before incorporating them into my teaching practices.
I take responsibility for any mistakes that may arise while incorporating AI into my teaching practices.
I assess the accessibility and reliability of the AI tool in advance before applying it to my classes.
I carefully evaluate the information provided by AI before incorporating it into my class.
I conform to ethical practices while using AI tools in my class.
I make sure AI is used appropriately in class.
I ensure that only reliable AI tools are used as learning materials in my teaching.
Professional Integrity (PI)
I provide clear guidelines to students on the ethical use of AI-generated content in their academic work.
I am responsible for monitoring the ethical implications of using AI and adjusting as needed to ensure fair practices.
I teach students to use AI in a way that respects rules and values.
I teach students how to use AI correctly, ensuring they understand the importance of honesty and fairness in their work.
I make sure to keep students' personal information safe when using AI tools for teaching.
I am responsible for building trust in AI tools and ensuring they are used ethically in class.
I take steps to protect students' information and use AI tools that comply with relevant regulations.
I am responsible for the choices made with AI tools in class.
Dependency
Educator Preparedness (EP)
I am prepared to incorporate AI tools into my teaching practices.
I am positive about integrating AI tools into the learning process.
I am confident in adapting new developments in AI learning tools.
I am patient with continuously learning new developments in AI tools to enhance my teaching practices.
I feel well-equipped to use AI effectively in the classroom.
I often consider their limitations, risks, and ethical guidelines when using AI tools in my teaching practices.
I am open and flexible when dealing with students' concerns about AI tools.
Knowing and having enough experience with AI, I am positive about incorporating AI tools into my teaching practices.
Institutional Support (IS)
The institution provides accessible training sessions on AI integration.
The institution provides clear guidelines and resources for incorporating AI into lesson plans.
The institution has the necessary technological setup to support the use of AI.
The institution provides opportunities like online courses and collaborative projects to learn about AI tools and integrate them.
The institution supports using AI effectively, including helping understand concepts and tools.
The institution provides training, seminars, and AI workshops about effectively incorporating AI tools.
The institution ensures I feel confident integrating AI tools into the classroom by offering ongoing support and facilitating hands-on experiences.

CRediT authorship contribution statement

Joanne Jorolan: Writing – original draft, Validation, Software, Resources, Formal analysis, Data curation, Conceptualization. **Florejane Cabillo:** Writing – original draft, Validation, Software, Formal analysis, Data curation, Conceptualization. **Renna Rose Batucan:** Writing – original draft, Visualization, Methodology, Data curation, Conceptualization. **Cherish Mae Camansi:** Writing – original draft, Validation, Data curation, Conceptualization. **Angela Etoquilla:** Writing – original draft, Visualization, Data curation, Conceptualization. **Jessieca Gapo:** Writing – original draft, Resources, Data curation, Conceptualization. **Danica Kaye Hallarte:** Writing – review & editing, Software, Methodology, Formal analysis. **Masza Lyn Milano:** Writing – review & editing, Software, Methodology, Formal analysis. **Roselyn Gonzales:** Writing – review & editing, Validation, Supervision, Methodology, Formal analysis. **Gamaliel Gonzales:** Writing – review & editing, Supervision, Software, Project administration, Methodology, Formal analysis, Conceptualization.

Declaration of generative AI and AI-assisted technologies in the writing process

While preparing this work, the authors used ChatGPT to enhance language fluency and readability. After using this tool, the authors reviewed and edited the content as needed and took full responsibility for the content of the published article.

Funding

This research did not receive any specific grant from funding agencies in the public, commercial, or not-for-profit sectors.

Declaration of competing interest

The authors declare no competing interests.

Data availability

Data will be made available on request.

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