Design and validation of an instrument to evaluate transformational and managerial leadership in the responsible use of artificial intelligence in educational centers

Diseño y validación de un instrumento para evaluar el liderazgo transformacional y directivo en el uso responsable de la inteligencia artificial en centros educativos

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Resumen

A medida que las herramientas de Inteligencia Artificial (IA) y de Inteligencia Artificial Generativa (IA-Gen) se consolidan como elementos centrales en la educación, el liderazgo escolar efectivo se vuelve esencial para garantizar una integración responsable y ética. Este estudio desarrolla y valida un instrumento psicométrico destinado a evaluar las percepciones del profesorado sobre el liderazgo de sus equipos directivos en la adopción de la IA y la IA-Gen, fundamentado en las teorías del liderazgo transformacional y ético. El instrumento contempla cuatro dimensiones clave (Liderazgo empoderado, Orientación, Precaución, y Colaboración-Cultura) y fue aplicado a una muestra de 470 docentes en ejercicio en España, cuyos datos fueron analizados mediante análisis factorial exploratorio y confirmatorio, revelando una estructura robusta de cuatro factores con alta fiabilidad (consistencia interna) y un adecuado ajuste del modelo. La validez convergente y discriminante confirmó la solidez psicométrica del instrumento, cuyas aplicaciones prácticas incluyen diagnosticar la preparación del liderazgo para la transformación digital, identificar necesidades de desarrollo profesional y orientar políticas de integración de la IA en los centros educativos. Asimismo, el estudio aporta al marco teórico del liderazgo educativo en entornos potenciados por la IA, destacando que la adopción exitosa no depende únicamente del acceso a la tecnología, sino de un liderazgo visionario, de apoyo y con fundamentos éticos.

Palabras clave: Inteligencia Artificial (IA); Centros educativos; Instrumento; Liderazgo; Liderazgo transformacional.

Abstract

As Artificial Intelligence (AI) and Generative AI (GenAI) tools become integral to education, effective school leadership is critical for ensuring their responsible and ethical integration. This study develops and validates a psychometric instrument to assess teachers' perceptions of their management teams' leadership in GenAI adoption, grounded in transformational and ethical leadership theories. The instrument measures four key dimensions: Empowering Leaders, Orientation, Caution and Collaboration-Culture. Data from 470 in-service teachers from Spain were analyzed using exploratory and confirmatory factor analyses, revealing a robust

four-factor structure with strong reliability (internal consistency) and good model fit. Convergent and discriminant validity further supported the instrument's psychometric soundness. Practical applications include diagnosing leadership readiness for digital transformation, identifying professional development needs, and guiding policy on AI integration in schools. The study also contributes to theoretical frameworks on educational leadership in AI-enhanced environments, highlighting that successful adoption depends not merely on technological access but on visionary, supportive, and ethically grounded leadership.
Keywords: Artificial Intelligence (AI); Educational centres; Instrument; leadership; Transformational leadership; teachers

1. Introduction

In the 21st century, Information and Communication Technologies (ICT) have gained significant global relevance, becoming key elements in the educational field. Woyo et al. (2020) highlight that teachers face constant pressure to incorporate educational innovations into school practices, since the continuous emergence of new technologies imposes challenges on both educational leaders and teaching staff, who must prepare students to operate with these emerging tools. To adequately respond to the educational demands of this digital transformation, headmasters are required to assume a technological leadership role (Adams, 2018) since this is a critical factor in achieving school effectiveness (Gurr et al., 2021), while teachers must act as facilitators in the pedagogical use of ICT.

Digital transformation in organizations fundamentally involves the incorporation of a set of technologies such as the Internet of Things (IoT), Artificial Intelligence (AI), Machine Learning, and the analysis of large volumes of data (Big Data) (Antonopoulou et al., 2021). In the educational context, one of the most disruptive technologies that is significantly changing the dynamics of teaching and learning is AI and, even more recently, its generative tools (GenAI) (Galindo-Domínguez et al., 2024; de la Flor Bancalero et al., 2026). Herold (2019) points out that, in the next decade, AI is expected to take over around 40% of the functions currently performed by teachers, mainly those that are not directly related to teaching, such as monitoring students' academic progress. Furthermore, according to Bryant et al. (2020), AI tools could significantly reduce teachers' workload, freeing up around 13 hours a week (approximately one-third of their workday) so that teachers can focus on more human aspects of their work, such as motivating students through personal relationships and working as a team with other teachers. In other words, AI is positioning itself as a leading technology, due to its potential to enrich or challenge the educational experiences of both students and teachers (Chen et al., 2020), so "leaders are key pillars in the development of a digital culture of a modern organization" (Antonopoulou et al., 2021, p. 1), in our case, in an educational organization.

Research on leadership in educational contexts has highlighted the fundamental role that leaders play in the continuous improvement and overall effectiveness of school institutions. The author Guardiola (2024) reflects that "educational leadership is not about being in charge; it is about taking care of those in your charge" (p. 1), so consequently, leadership should not focus solely on exercising authority, but on accompanying, supporting and empowering the members of the educational organization to achieve comprehensive and sustainable development in the school environment (Iqbal & Piwowar-Sulej, 2022). In particular, transformational leadership has been identified as a key approach to driving these significant changes. Jensen et al. (2019) points out that a transformational leader is one who builds a clear vision of the fundamental objectives of the organization (1), strives to share that vision with team members (2), and constantly works to sustain this shared vision over time (3). Bass (1990) defined it as the type of leadership that mobilizes followers by expanding their commitment to the community, generating adherence to a collective mission, and inspiring them to prioritize group interests over individual ones. In this sense, transformational leadership could be understood by the headmaster of an educational organization as a set of behaviours aimed at developing, communicating, and maintaining a shared vision.

This approach is particularly relevant in the current context of digital transformation, where the use of AI-GenAI tools helps redefine teaching and learning processes. So far, studies have shown that AI has the potential to enrich the educational environment by fostering both interest in learning and boosting creativity in both teachers and students (Mohamed et al.,2025), facilitating more effective classroom management (Ahmad et al., 2022), and offering personalized learning support to students' needs (Tapalova & Zhiyenbayeva, 2022). For these tools to be effectively integrated into classrooms, it is essential that headmaster at educational centers exercise transformational leadership that motivates, accompanies, and trains teachers in the pedagogical use of these technologies, thus fostering a culture of sustained innovation aligned with the challenges of the 21st century. In this context, Wang (2021) points out that AI tools have the potential to optimize decision-making by school leaders and to guide the approach beyond conventional digitalization. However, despite the growing interest in the use of AI-GenAI applications in education, their specific application to educational leadership has been poorly explored so far.

Currently, there are few adequate frameworks to guide educational leaders in developing effective technological leadership through the use of AI-GenAI applications. One of the most internationally recognized benchmarks is the International Standards for Educational Leaders (ISTE, 2018), which is widely used both to assess technological leadership and to guide training processes in this area. This framework describes in detail the key competencies a technology leader must possess; however, it does not specifically address the use of AI-GenAI. On the other hand, the instrument proposed by Bronkhorst & Becker (2024) evaluates leadership competencies with the use of AI but does not focus on the figure of the headmaster or his or her ability to exercise transformational leadership within the educational center. Likewise, the study by Kokkonos et al. (2025) presents an instrument focused on digital technologies and leadership practices, although it does not specifically address the role of the headmaster in integrating AI-GenAI into school dynamics. Based on the analysis of current scientific literature, a clear lack of psychometric instruments has been identified, which are designed to measure the teachers' perception of the role of the management team in promoting, guiding and responsible managing the use of AI-GenAI tools in teaching-learning and management processes.

Therefore, the purpose of this study is to validate a psychometric instrument with sufficient methodological rigor to assess teachers' perceptions of management team (director, head of studies and secretary) in educational contexts mediated by AI-GenAI. Furthermore, it is intended that this instrument serve as a basis for future training actions, institutional strategies, and decision-making aimed at a coherent, ethical, and effective digital transformation in educational centres.

2. Theoretical Framework for the Instrument Construction

The conceptual framework of this psychometric tool combines the traditional and modern views on educational leadership, which, in this particular case, is contextualized to the new challenges of AI-GenAI implementation. It is organized upon four dimensions of critical leadership based on the literature that are considered vital to the responsible use of these technologies in schools.

1. Empowering Leadership. Empowerment of teachers is the core concept of the process of effective school leadership ensuring the personal competence and the possibility of its demonstration in the organization (Short, 1998). This means providing the environment conducive to the intrinsic motivation and psychological empowerment (Joo et al., 2017) by adopting the practices that enhance the perceived autonomy and competence of teachers (Dou et al., 2017; Khan, 2025). This empowerment is positively related to transformational practices, including presenting a clear vision, behaviour modeling, and the occupation of common goals (Stanescu et al., 2021; Tore and Uzun, 2024). The role of leadership in the context of AI-GenAI should thus not only include advancing technical competency but also encourages and aids teachers to explore and use these tools ethically and pedagogically and surpass mere delegation to actual enablement.

2. Guidance and Mentorship. Technology integration constitutes a process that demands leaders that do more than just teach the technicalities; they should be able to teach the pedagogy and emotional aspects of the same. The teachers are seeking collegial support and leaders who can counteract external pressures to focus on the social dynamics of the school (Blossing & Liljenberg, 2019; Leo, 2015). The leader has to create optimism and confidence in the school vision by influencing others (Nwakoby, 2025) towards achieving education goals. Technology management can be translated to empower staff to perceive, analyze, and implement technology successfully (Daugherty et al., 2013; Yuting et al., 2022), which requires particular digital, pedagogical, and administrative skills (Salendab & Dapitan, 2021). In the case of AI-GenAI, the guidance should include holistic assistance that covers technical expertise and the pedagogical redesign of the processes of teaching and learning.

3. Ethical Caution and Critical Oversight. The high rate of AI implementation requires a top management approach of critical concern and high level of ethics. Ethical leaders are also fair, full of integrity, and honest, and they stress the importance of ethical conduct in decision-making (Brown & Treviño, 2006; Ehrich et al., 2015). This constitutes an ethical requirement to promote the best learning and a positive school culture (Starratt, 2004). Particularly to AI, leaders should take a proactive stance in addressing the risks, including algorithmic bias that jeopardizes educational equity (Ghamrawi et al., 2024), implementing effective data protection measures to protect privacy (Igbokwe, 2024; Zawacki-Richter et al., 2019), and developing legal and training systems to use it safely (Kafa, 2025). This dimension embodies the proactive involvement of the leader in creating a critical and risk-averse attitude towards the adoption of AI-GenAI.

4. Fostering Collaborative Culture. Ultimately, a solution based on a joint school culture with a shared vision is the only way to integrate AI sustainably. There is an indirect connection between school culture and the use of technology because it can be supported by leaders and support services (Gürfidan & Koç, 2016). The key to developing an institutional culture and objectives to change is an effective leader (Gurr & Drysdale, 2020; Maddula, 2018). An excellent digital culture encourages collaboration, creativity, and lifelong learning (Deal & Peterson, 2009), which is also needed to be applied to technological experimentation and knowledge management in the age of AI. The

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leadership should thus be able to establish participatory learning spaces that foster trust and belonging to allow the educational community to overcome AI challenges as a whole without sacrificing the human aspect that education entails (Hernandez & Esquivel, 2024).

Instrument Structure. In this regard, the constructed tool is organized into four dimensions in line with it: (A) Empowering Leaders (inspiring and enabling faculty to use AI-GenAI); (B) Orientation (to provide pedagogical and technical direction); (C) Caution (to ensure critical, secure, and ethical implementation); and (D) Collaboration and Culture (to build a shared vision and trusting community in using AI-GenAI). Such a framework will ensure that the measurement tool quantifies the individual, multifaceted leadership behaviors necessary to responsibly integrate AI-GenAI in learning institutions.

3.Method

3.1 Design and Participants

This study employed a non-experimental, ex post facto design with purposive sampling, a methodological approach particularly suited for examining teachers' natural perceptions of leadership in AI integration without experimental manipulation. The study sample consisted of 470 in-service teachers from Spain. Table 1 shows the distribution by educational stage, sex and average age of each group. Data collection occurred via secure anonymous online surveys with comprehensive ethical protections including voluntary participation, withdrawal rights, and encrypted data storage.

Table 1

Sample distribution

	Male		Female	
	N	Age	N	Age
Educational Stage				
Early childhood education	2.7% (1)	55.00	97,3% (36)	46.11±8.10
Primary education	32.3% (52)	44.77±9.23	67,7% (109)	46.77±9.13
Secondary education	42.2% (65)	47.31±10.05	57,8% (89)	47.60±9.17
Adults	31.6% (6)	47.50±7.82	68,4% (13)	49.92±10.40
Vocational training	50.0% (21)	44.86±9.13	50,0% (21)	46.71±9.68
Language schools and music conservatories	29.8% (17)	49.00±8.53	70,2% (40)	49.85±8.21
Type of territory				
Urban	76.50% (124)	46.28±9.70	68.20% (210)	48.00±8.66
Rural	23.50% (38)	46.82±8.70	31.80% (98)	46.32±9.67

Note: own elaboration

3.2 Procedure and verification of assumptions

Exploratory and confirmatory factor analyses were used in a sequential analytical approach to assess the construct validity of the instrument. The original purpose of exploratory factor analysis (EFA) was to look at the items' underlying structure and find possible latent factors by analyzing their intercorrelations (Sencan, 2005). This method is consistent with the basic psychometric principle that a smaller number of unobserved factors can account for observed item correlations (Mulaik, 2018). Principal axis factoring with Oblimin rotation was used in the analysis, which allowed for the determination of the factor structure, including the number of significant dimensions and

their relationships, as well as the examination of shared variance (Mvududu & Sink, 2013).
The proposed factor structure was then examined using Confirmatory Factor Analysis (CFA). To meet the CFA requirements, multivariate normality was checked using Mardia's coefficient. Using the formula p (p + 2), where p is the number of items, the values fell below the crucial cutoff of 360 (Bollen, 1989). The final 18-item instrument's coefficient of 123.963 indicated that the data satisfied the multivariate normality assumption. Following the CFA, various indices were employed to assess internal consistency and reliability. Cronbach's alpha, Spearman-Brown, Guttman's Lambda, McDonald's Omega, and Composite Reliability were among them. All the items were rated on a 7-point Likert scale, where 1 denoted "totally disagree" and 7 denoted "totally agree".

4. Results

4.1 Descriptive Analyses

To evaluate the data to be used subsequently on psychometric analysis we initially considered the item-level descriptive index and distribution character.

- *Variability of Items:* Each of the items showed a high level of variability to be analyzed with standard deviations (SD) being more than the suggested value of >1 (Meroño et al., 2018).
- *Normality Test:* To test the univariate normality of each item, we looked at skewness (S) and kurtosis (K) values. In order to use a rigorous criterion, we used strict thresholds (-1, 1) used by Ferrando and Anguiano-Carrasco (2010) and Muthén and Kaplan (1985) in majority of the dimensions. And in the case of Dimension C, a more relaxed criterion would at times be appropriate in applied research of leadership, we used the broader (1.5, -1.5) limit (Forero et al., 2009).
  Item Retention and Elimination: According to this assessment, items A1, A3, A4, A5, A6, A8, A10, A11, A13, B3, B10, D3, and D7 were dropped in Dimensions A, B, and D since their skewness and kurtosis values were out of range (Strict (1 -1)). D2, D8, and D9 were kept to be further analyzed since their values were within the limits of the acceptable value. The items that constituted Dimension C were all within the relaxed criterion and were retained. This pre-screening served as a strong base to the subsequent factor analyses.

Given the relevance of normality to factor analysis, it was necessary to justify the removal of items that exceeded these thresholds. Items displaying extreme skewness or kurtosis were excluded because such deviations can distort factor loadings, inflate communalities, and compromise the stability and interpretability of the factorial solution. Ensuring adequate normality at the item level therefore provided a more robust basis for the exploratory factor analysis carried out in the next stage. Table 2 shows all these results.

Table 2

Initial version of the instrument

	SD	*S*	*K*
DIM. A - Empowering Leaders (Leadership team push to integrate AI-GenAI into the school)			
A1-The management team encourages teachers to use AI-GenAI tools to create multimedia materials as a teaching resource (creation of texts, videos, multimedia presentations, images, etc.).	2.05	.18	-1.26
A2-The management team encourages teachers to use AI tools for planning the teaching process (such as DreamBox ClickUp, LessonPlans.ai, Learnt.ai, PlanifAI, among others)	1.94	.54	-.94
A3-The management team encourages teachers to use AI tools for learning assessment (such as Exam.net, Quizizz, Kahoot AI Reports), motivating the exploration of new technological tools.	1.99	.22	-1.18
A4-The management team values the efforts of teachers who use AI to innovate in their teaching.	2.04	-.03	-1.26
A5-The management team motivates teachers to integrate AI tools to monitor students' academic progress (such as Moodle Analytics).	1.96	.28	-1.17
A6-The management team encourages teachers to use AI tools to dynamically adjust activities (such as Kahoot AI or Nearpod) based on students' responses and needs in real time.	2.04	.23	-1.24
A7-The management team encourages teachers to use AI tools to identify patterns in student data (such as Microsoft Insights or DataRobot) in order to develop specific teaching strategies.	1.89	.63	-.80
A8-The management team encourages teachers to use AI tools such as Canva AI or Adobe Firefly to generate interactive images and presentations that enrich the teaching process.	2.10	.11	-1.38
A9-The management team encourages the use of AI tools such as Synthesia or HeyGen for the creation of educational videos with avatars and automated voiceovers.	1.87	.73	-.63
A10-The management team promotes the use of AI tools such as ChatGPT, Geminis, or Copilot to generate educational texts adapted to different learning levels.	2.11	.21	-1.33
A11-The management team encourages the use of AI platforms such as Genially or Prezi AI for teachers to design dynamic and interactive presentations that capture students' attention.	2.09	.11	-.136
A12-The management team encourages teacher training and development in AI and Generative AI, organizing workshops on the use of tools such as Synthesia for the creation of automated educational videos.	1.97	.49	-1.00
A13-The management team's efforts to generate a culture of digital innovation in the school are recognized, including the use of emerging tools such as AI.	1.99	.15	-1.25
DIM B- Orientation (Leadership and guidance of the management team in the use of AI-GenAI)			
B1-The management team provides clear guidelines on how to use artificial intelligence to monitor students' academic progress.	1.84	.77	-.50
B2-The management team instructs teachers on the appropriate use of artificial intelligence in the creation of multimedia resources that promote personalized learning.	1.91	.70	-.66
B3-The management team facilitates access to resources and training on artificial intelligence to strengthen the production of educational content and improve teaching.	2.02	.34	-1.16
B4- The management team guides teachers on how to use AI to improve formative and summative assessment processes.	1.89	.69	-.64
B5-The management team promotes the optimization of teachers’ work through AI, reducing administrative load and allowing greater focus on teaching.	1.95	.54	-.95

B6-The management team advises teachers on how to apply AI to optimize time management in grading, student monitoring, and lesson planning.	1.90	.72	-.67
B7-The management team provides specific guidance to newly hired teachers on using AI in teaching and educational management.	1.83	.77	-.53
B8-The management team offers suggestions to teachers on how to improve their pedagogical practice through AI training and classroom application.	1.95	.60	-.87
B9-The management team provides resources and technical support for the implementation of AI in teaching.	1.95	.52	-.94
B10-The management team offers spaces for dialogue and reflection on the impact of AI in teaching practice.	1.95	.45	-1.04
B11-The management team maintains fluid communication with teaching staff regarding the evolution of AI in education.	1.94	.51	-.95
B12- The management team guides the educational community on the transformation AI brings to teaching models, promoting a proactive and adaptive approach.	1.92	.58	-.91
B13-The management team guides the educational community on the social and ethical impact of AI use in education and society.	1.98	.55	-.99
DIM C- Caution (Risk and challenge management of AI-GenAI in education)			
C1- The management team promotes responsible and ethical use of AI in teaching and school management.	2.16	.03	-1.37
C2- The management team warns about potential biases and limitations of AI in education.	2.15	.12	-1.38
C3-The management team encourages the protection of personal data when using AI tools.	2.26	-.09	-1.47
C4-The management team promotes critical thinking about the results generated by AI in education.	2.16	.03	-1.36
C5-The management team takes measures to prevent the misuse or illegal copying of AI software in school.	2.17	.20	-1.34
C6-The management team ensures that AI software used in school has legal licenses and complies with current regulations.	2.19	.13	-1.39
C7-The management team promotes the development of critical digital skills among teachers and students for safe and responsible AI use.	2.12	.08	-1.32
C8-The management team ensures that the use of AI in school respects copyright and academic integrity in educational content production.	2.19	.08	-1.39
DIM D- Collaboration and Culture (Building Community Around AI-GenAI)			
D1-The management team promotes collaboration among teachers to design educational projects with AI.	1.98	.43	-.99
D2-The management team values and publicly shares the achievements of the teaching staff in the implementation of AI.	2.08	.47	-1.09
D3-The management team manages the presence of guest speakers to raise awareness about the risks, opportunities and best practices in the use of artificial intelligence.	2.11	.47	-1.13
D4-The management team encourages the creation of collaborative work networks with other centers on good practices in educational AI.	1.98	.71	-.72
D5-The management team encourages spaces for dialogue between families, teachers and students on the impact of AI on education.	1.97	.64	-.83
D6-The management team encourages the participation of the entire educational community in defining the center's AI strategies.	1.97	.62	-.84
D7-The management team creates a positive school climate to experiment with AI without fear of error.	2.10	.32	-1.25
D8-The management team organizes training courses on artificial intelligence aimed at teachers, students, and families.	2.05	.51	-1.06
D9-The management team invites external experts to give talks on the ethical and responsible use of artificial intelligence in education.	2.08	.59	-1.00

Note: own elaboration

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The discriminative power of each item was evaluated through corrected item-total correlation analysis, examining the relationship between individual item scores and their corresponding latent factors. This methodological step serves to enhance factor reliability by identifying potentially weak items for potential removal. Following established psychometric standards (Shaffer et al., 2010), we applied a conservative threshold of 0.40 for item retention. As presented in Table 3, all items demonstrated strong discriminative capacity, with corrected item-total correlations exceeding 0.79 - well above the recommended minimum. The analysis also examined Cronbach's alpha values for each potential item deletion, confirming that no item removal would improve enormously scale reliability. Consequently, all items were retained in the final instrument, as each contributed significantly to the overall measurement quality of their respective factors.

Table 3

Analysis of the scale discrimination index

	Mean scale if item has been deleted	Scale variance if item has been suppressed	Corrected total item correlation	Cronbach's alpha if the item has been deleted
DIM A - Empowering Leaders (Leadership team push to integrate AI-GenAI into the school)				
A2	95.9277	2487.496	.791	.987
A7	96.1021	2495.081	.773	.987
A9	96.1979	2494.837	.782	.987
A12	95.8489	2484.397	.798	.987
DIM B- Orientation (Leadership and guidance of the management team in the use of AI-GenAI)				
B1	96.2043	2483.020	.863	.986
B2	96.1000	2475.800	.867	.986
B4	96.0787	2477.868	.867	.986
B5	95.9298	2470.709	.877	.986
B6	96.1340	2474.756	.878	.986
B7	96.2298	2479.627	.887	.986
B8	95.9979	2470.736	.879	.986
B9	95.8362	2474.414	.858	.986
B11	95.8681	2468.281	.895	.986
B12	95.9936	2469.158	.901	.986
B13	95.9191	2466.569	.886	.986
DIM C – Caution (Risk and challenge management of AI-GenAI in education)				
C1	95.0702	2458.918	.845	.987
C2	95.2340	2457.519	.855	.986
C3	94.8936	2460.308	.801	.987
C4	95.1766	2456.700	.858	.986
C5	95.3596	2459.391	.839	.987
C6	95.2489	2468.307	.790	.987
C7	95.1809	2459.232	.862	.986
C8	95.1894	2457.685	.839	.987
DIM D- Collaboration and Culture (Building Community Around AI-GenAI)				
D1	95.6936	2472.840	.854	.986
D2	95.7681	2462.865	.858	.986
D4	96.0660	2476.736	.831	.987
D5	96.0319	2480.602	.815	.987
D6	96.0213	2475.565	.844	.987
D8	95.8447	2473.121	.819	.987
D9	95.8894	2479.672	.774	.987

Note: own elaboration

Table 4 presents the matrix of factorial correlations between the four latent factors of the instrument, calculated using the oblimin rotation method. The results show high and significant correlations between the latent factors: for example, between the Empowering Leaders factor and the Caution factor, the correlation is .583; between the Empowering Leaders factor and the Orientation factor, it is .719; between the Caution and Orientation factors, it is .779, between the Caution and Collaboration and Culture factors, it is .754; between the Orientation and Collaboration and Culture factors, it is .793, and between the Empowering Leaders and Collaboration and Culture factors, it is .701. These correlations indicate that the factors are not completely independent of each other, justifying the use of an oblique rotation such as oblimin.

Table 4

Factorial correlation matrix

Factor	DIM B- Orientation	DIM C - Caution	DIM D- Collaboration and Culture	DIM. A - Empowering Leaders
DIM B- Orientation	1.000			
DIM C - Caution	.779	1.000		
DIM D- Collaboration and Culture	.793	.754	1.000	
DIM. A - Empowering Leaders	.719	.583	.701	1.000

Note: Own elaboration

4.2 Exploratory Factor Analysis (EFA)

We used exploratory factor analysis (EFA) to check the construct validity, complying with the methods applied in similar studies (Guillén Gámez et al., 2024; Soriano-Alcantara et al., 2024; Romero Martínez et al., 2020; Guillen-Gamez et al., 2021) and the protocols set out by Gümüş & Kukul (2023). We used the Kaiser-Meyer-Olkin (KMO) index and Bartlett's test of sphericity to see if the data was good for factor analysis and if the sample size was big enough. Worthington & Whittaker (2006) state that a KMO score above 0.8 indicates a sample of good quality. In this case, a score of 0.975 was achieved, indicating that the sample was highly suitable. Bartlett's test, on the other hand, was statistically significant (p. < .05), with a chi-square value of 21,613.843 and 406 degrees of freedom. This indicated that there were sufficient correlations between the variables to proceed with the analysis. According to Watkins (2021), these results are good enough for the EFA.

The EFA was applied to 30 items after preliminary analysis. The literature suggests keeping factors with eigenvalues (λ) greater than one (Cattell, 1966). Table 5 shows that four components with eigenvalues greater than one explained 86.20% of the instrument's variation. First component explains 73.05% of the variance, second 6.26%, third 4.711%, and the fourth factor 2.71%.

Table 5

Total variance explained

Number of latent factors	**Total**	**% variance**	**% accumulated**
1	21.184	73.049	73.049
2	1.816	6.261	79.310
3	1.211	4.176	83.486
4	1.006	2.711	86.197

Note: Own elaboration

After the prescribed threshold, factors with factor loading values lower than 0.40 or those that were cross-loaded were marked for exclusion (Gumus & Kukul, 2023). As indicated in Table 6, all items met these criteria, and no additional eliminations were necessary. The final factors model was clearly consistent with the four theoretical dimensions:

1. Factor 1 (Dimension B - Orientation): Items B2, B7, B8, B4, B6, B9, B1, B12, B13, B5, B11.
2. Factor 2 (Dimension C - Caution): Items C3, C8, C4, C7, C1, C6, C2, C5.
3. Factor 3 (Dimension D - Collaboration and Culture): D5, D4, D6, D8, D9, D2.
4. Factor 4 (Dimension A - Empowering Leaders): Items A2, A7, A12, and A9.

Factor loadings for item C3 greater than 1 have also been observed. In factor analysis with oblique rotation, the factor loadings of the pattern matrix cease to represent simple correlations since "they are regression coefficients, they may be greater than unit" (Cudeck, 2000, p.271), although values > 1 are rarely observed, so their behavior should be monitored in subsequent analyses.

Table *6*

Factor analysis of the instrument

	Factor Nº 1 (DIM-B Orientation)	Factor Nº 2 (DIM-C Caution)	Factor Nº 3 (DIM-D Collaboration and Culture)	Factor Nº 4 (DIM-A Empowering Leaders)
B2	.973			
B7	.950			
B8	.938			
B4	.917			
B6	.872			
B9	.814			
B1	.810			
B12	.785			
B13	.778			
B5	.759			
B11	.753			
C3		1.015		
C8		.925		
C4		.919		
C7		.877		
C1		.874		
C6		.860		
C2		.855		
C5		.823		
D5			.972	
D4			.923	
D6			.881	
D8			.712	
D9			.595	
D2			.578	
A7				.847
A9				.830
A2				.551
A12				.497

Note: Own elaboration

4.3 Confirmatory Factor Analysis (CFA) for Construct Validity

To analyze and validate the accuracy of the four factors identified in our study, several CFAs were conducted. The goal was to create an instrument that was as clear and concise as possible, reducing the number of items without negatively affecting its reliability or validity (Bandalos & Finney, 2018). First, an initial model based on the final latent structure identified through the EFA was evaluated. However, as can be seen in Table 7, this model did not meet the fit indices recommended by Hu & Bentler (1999), which led to the development of a second model. In this new proposal, those items that presented an excessively high covariance with other items in the instrument were eliminated, following the methodological recommendations of Byrne (2013): B6, B9, B12, B13, B5, B11, C8, C7, C5, D5, D9.

Table 7

Model goodness-of-fit indicators

Models	*CMIN*	*gl*	*C.M./df*	*IFI*	*CFI*	*TLI*	*NFI*	*RMSEA*	*SRMR*
1º	2331.024	399	5.842	.914	.914	.906	.898	.102	.0382
2	396.480	127	3.122	.977	.977	.973	.967	.067	.0313

Note: Own elaboration

The overall excellent fit was also confirmed by the final CFA model, based on a set of comprehensive fit indices. The main fit statistics are entered in Table 7, and their analysis against set standards is discussed below. The absolute fit was strong. The value of the relative chi-square (χ^2/df) was 2.006, which is significantly less than the conservative level of 3.00 and indicates a good model (Kline, 1998). What is more, the fit indices were approximated and met or even surpassed the desirable levels: the value of the RMSEA equal to.067 is not much larger than the acceptable range (.05 to .08) (MacCallum et al., 1996), whereas the value of SRMR of. 0.313 is much less than the cutoff threshold of 0.08 that defines a good fit (Hu & Bentler, 1999).

The model was also robust because of incremental and comparative fit indices. The CFI (.977), IFI (.977), and TLI (.973) all exceeded the 95% mark of an excellent fit (Hu & Bentler, 1999; West et al., 2012), and a value near the ideal mark of 1 also affirms the model. In short, all of the assessed indices were consistent in showing that the ultimate four-factor model is a valid and appropriately fitting measure of the construct. This last factor model is in Figure 1 where the standardized relations between the latent factors and the observed items of these factors are shown.

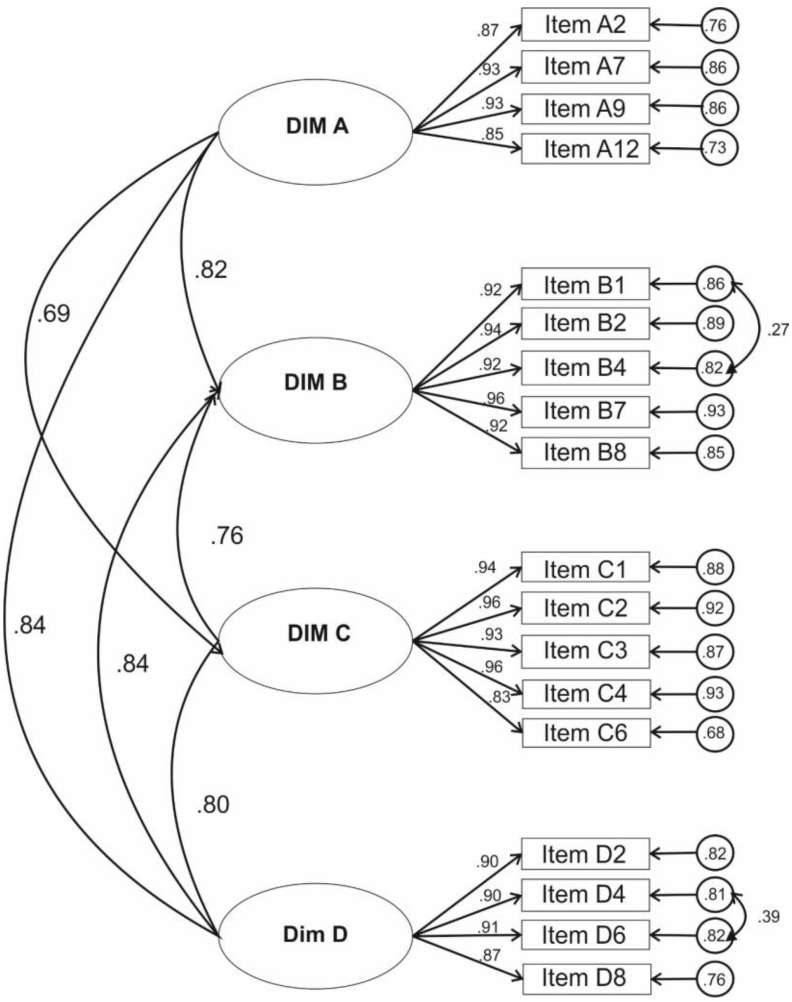

Figure 1

Confirmatory Factor Analysis Diagram

4.4 Convergent and discriminant validity

In further supporting the validity of the instrument, we evaluated the construct validity of the instrument as well as the discriminant validity against the criteria outlined by Fornell and Larcker (1981) and Hair et al. (2010). Convergent validity was studied through the Average Variance Extracted (AVE). All four dimensions scored above the 50 mark - Dimension A (.802), Dimension B (.877), Dimension C (.855), and Dimension D (.802) (see Table 8). This shows that on average, every latent construct has more than half the variance in its indicators, which is a strong internal coherence.

Two complementary tests were used to assess discriminant validity which guarantees that the dimensions are different. To start with, the square root of the AVE of each dimension (between.896 and .936) was high compared to the correlations with all other dimensions (Table 8). Second, the Maximum Shared Variance (MSV) of each construct was smaller than its own AVE (e.g., in the case of Dimension A: MSV. .711 < AVE. .802). The combination of these results meets the Fornell-Larcker criterion well giving strong evidence that each of the factors in the model measures a distinct construct that is not reflected in the rest.

Altogether, the analyses indicate that the four-factor design of the instrument shown by both high internal consistency (convergent validity) and obvious empirical differentiation (discriminant validity) support the soundness of the measurement model.

Table 8

Convergent and discriminant validity coefficients

	AVE	MSV	DIM-A Empowering Leader	DIM-B Orientation	DIM-C Caution	DIM-D Collaboration and Culture
DIM-A Empowering Leaders	.802	.711	.896			
DIM-B Orientation	.877	.708	.824***	.936		
DIM-C Caution	.855	.635	.693***	.758***	.925	
DIM-D Collaboration and Culture	.802	.711	.843***	.841***	.797***	.896

Note: Own elaboration. *** $p < 0.001$

4.5 Reliability analysis

Internal consistency of the instrument was strictly evaluated through the calculation of a number of internal consistency coefficients of every dimension and the complete scale. The four dimensions were found to be very reliable and much better than the set standards. Each dimension had Cronbach alpha (as shown in Table 9) of above .90, which is significantly greater than the desired level of .80 (Cokluk et al., 2012) and the acceptable minimum of .70 (Nunnally, 1994). Composite Reliability (CR) also supported this high internal consistency with all the values of more than .70 (Heinzl et al., 2011).

Three other coefficients were looked into in order to provide robustness:

- Omega (ω) of McDonald was between .95 and .98 across the dimensions and this shows that there is excellent consistency and the findings are compatible with the findings of Cronbach alpha.
- Both the split-half coefficients of Spearman-Brown and Guttman were found to be in recommended standards in all the dimensions which confirmed the stability of the measurement.

To conclude, convergent evidence of various measures of reliability gives a good and cohesive evidence that the instrument has very high levels of internal consistency both at the dimensional level as well as at the global scale.

Table 9

Reliability coefficients

Dimension	DIM.A	DIM.B	DIM.C	DIM. D	TOTAL
Cronbach's alpha	.939	.973	.966	.946	.977
Spearman-Brown coefficient	.941	.964	.952	.939	.926
Split-half of Guttman	.941	.922	.912	.939	.925
Omega McDonald	.957	.986	.982	.952	.975
CR	.942	.973	.967	.942	-

Note: Own elaboration

4.6 Measurement Invariance Across Gender and Geographical Location

In multigroup invariance analysis, the fit indices χ^2, CFI and RMSEA are especially relevant because they help determine whether the measurement model operates in the same way across different groups (Byrne, 2010). In this study, we examined measurement invariance both by gender (male/female) and by type of territory (rural/urban).

The first step was to compare the unconstrained model (Model 1) with the model in which factor loadings were constrained (Model 2). When the difference between both models is not statistically significant ($p > .05$), it can be concluded that the model performs equivalently across groups. For gender, the result was p. = .879, indicating that the model behaved similarly for men and women. The same procedure was applied to the rural/urban groups, and the results also showed non-significant differences (p. = .369), supporting invariance across territories.

However, several authors have noted that the χ^2 difference test is overly strict (Cudeck & Browne, 1983). To address this limitation, Cheung & Rensvold (2002) recommend basing invariance decisions on the change in CFI between model 1 and 2, suggesting that invariance is supported when the decrease in CFI is smaller than .01. As presented in Table 10, the CFI values for all group comparisons (gender and territory) were identical across models 1 and 2, providing additional evidence that the measurement model is invariant for both men and women and for teachers from rural and urban contexts.

Table 10

Multigroup analysis of factorial invariance by sex and type of centre

Invariance by sex (male/female)									
Models	χ^2	*gl*	χ^2/gl	$\Delta\chi^2$	Δgl	CFI	IFI	TLI	RMSEA (IC90%)
1.Unconstrained	674.496	254	2.655	-	-	.965	.965	.958	.059 (.054-.065)
2.Measurement weights	682.693	268	2.547	8.197	14	.965	.966	.960	.058 (.052-.063)
3.Structural covariances	692.713	278	2.492	10.02	10	.965	.962	.962	.056 (.051-.062)
4.Measurement residuals	744.498	298	2.498	51.785	20	.963	.963	.962	.057 (.052-.062)
Invariance by territory (urban/rural)									
1.Unconstrained	659.734	254	2.597	-	-	.966	.966	.959	.058 (.053-.064)
2.Measurement weights	674.871	268	2.518	15.137	14	.966	.966	.961	.057 (.052-.062)
3.Structural covariances	696.043	278	2.504	21.172	10	.965	.965	.962	.057 (.051-.062)
4.Measurement residuals	800.735	298	2.687	104.69	10	.958	.958	.957	.060 (.055-.065)

Note: Own elaboration

5. Discussion

In the current educational landscape, where AI-GenAI tools are reshaping teaching and school management, educational leaders play a crucial role in guiding this digital transition. This study contributes to the literature by validating a novel psychometric instrument assessing teachers' perceptions of their management teams' leadership related to AI-GenAI integration. Unlike previous tools focused on general technological leadership, this instrument captures four targeted dimensions: institutional promotion and teacher empowerment (Empowering Leaders), pedagogical guidance (Orientation), ethical oversight (Caution) and building community around AI-GenAI (Collaboration and Culture).

A rigorous methodological validation confirmed that this scale can reliably assess digital learning leadership characteristics. EFA and CFA supported the hypothesized structural model, and the overall fit indices were acceptable (CFI = 0.977; RMSEA = 0.067), meeting established psychometric criteria (Hu & Bentler, 1999). All dimensions demonstrated strong internal consistency, and the results provided evidence of convergent and discriminant validity, as recommended by Hair et al. (2010). Furthermore, multigroup invariance analyses revealed that the measurement model functions equivalently across key demographic groups. Specifically, the scale showed gender invariance, with no significant differences between male and female teachers, and territorial invariance, indicating that the instrument performs similarly for teachers from both rural and urban contexts. This invariance evidence reinforces the robustness and generalizability of the instrument, confirming that its scores can be meaningfully compared across diverse teacher populations. Taken together, these findings demonstrate that the instrument is psychometrically sound, structurally stable, and appropriate for assessing digital learning leadership across different groups. The instrument's theoretical framework improves during validation:

- Transformational leadership is crucial for digital transformation, as Dimension A (Empowering Leaders) stood out. Transformational leaders create a shared vision, encourage commitment, and boost group effectiveness, according to Bass (1990). Jensen et al. (2019) supported this in digital learning contexts. The high connections in this category show that teachers respect leadership that fosters freedom, innovation, and trust. This supports empowerment ideas (Short, 1998; Stanescu et al., 2021). These views emphasize that school leaders need professional agency, intrinsic motivation, and a collaborative culture to handle technological challenges.
- Leadership behaviours in Dimension B (Orientation) include training, resources, and relational support. This suggests leadership goes beyond visionary rhetoric to include practical facilitation. Blossing & Liljenberg (2019) and Leo (2015) agree that excellent digital transition leaders must blend strategic guidance and hands-on coaching. Teachers appreciate leaders who simplify AI-driven instruction and provide ongoing, needs-based support. This supports psychological empowerment (Joo et al., 2017; Dou, 2017). This leadership enhances instructors' confidence, ensuring technology integration is useful and long-lasting.
- Meanwhile, dimension C (Caution) discusses AI-GenAI-driven education leaders' moral duties, such as data privacy, risk reduction, and bias awareness. The strong internal consistency of this dimension implies that moral leadership is becoming more crucial for digital transformation. Ehrich et al. (2015), Starratt (2004), and Igbokwe (2024) agree that school leaders should be ethical stewards who encourage fairness, openness, and responsibility in AI-GenAI use. Leaders can avoid unintentional harm and promote responsible innovation by incorporating ethical vigilance into institutions.
- Dimension D (Collaboration and Culture) highlights that effective AI integration requires shared commitment and community building. Leaders who promote collaboration, dialogue, and trust transform technological change into a collective process. This finding supports Gürfidan & Koç (2016) and Deal & Peterson

(2009), who emphasized that school culture mediates innovation and fosters continuous learning. Such leadership preserves the human dimension of AI adoption and sustainable educational transformation.

The scale shows a four-part leadership model of empowerment, guidance, ethical and collaboration stewardship that includes all the skills needed for AI-GenAI to be used in education. These dimensions are different but connected, which gives us a more nuanced understanding of how management team can deal with technological disruption while still being morally and pedagogically responsible. This framework not only moves theoretical discussions forward, but it also gives practitioners useful ideas on how to use AI in fair and transformative ways.

The instrument helps to fill a particular gap in the measurement of leadership when it comes to integrating AI in education. Available studies either determine AI competence among teachers and students (e.g., Reina-Parrado et al., 2025) or determine correlations between overall leadership styles and AI attitudes (e.g., Erdoğan et al., 2025). Other innovative methods combine AI with a particular leadership model, such as spiritual leadership (Khasawneh et al., 2025). Though these studies confirm the leadership-AI relationship, a measuring device that would evaluate the exact behaviours to be adopted in the implementation of responsible AI was lacking.

Our study develops this innovative instrument because it puts the traditional transformational and managerial models of leadership into perspective regarding the responsible use of AI-GenAI. This makes it a behavioral, rather than attitudinal, measure. The tool determines the ways leaders foster ethical vision (transformational) and governance systems (managerial) of AI-GenAI.

The study is methodologically strong, as it employs a sequential validation approach through mixed methods, ensuring the items are applicable to real-life leadership issues. What has been obtained is a psychometrically sound, two-factor instrument.

This contribution has three effects: (1) Theoretical: It is realized as a kind of measurement of the operationalization of a responsible AI-GenAI, not as an argumentative concept (e.g., Hou et al., 2024) but as a scale; (2) Practical: It is a diagnostic tool in the leadership development of schools; (3) Research: It provides a validated scale in the future, to relate specific leadership behaviour to outcomes in AI-GenAI integration.

5.1Pedagogical Implications

In educational institutions, the validated tool is used to (1) determine what AI-GenAI related skills leaders need to improve in transformational leadership, pedagogical mentoring, and ethical decision-making so they can get the right professional development; (2) empower teachers to ask for the right AI-GenAI implementation support; and (3) align pedagogical goals and technological integration. The tool promotes ethical and innovative company cultures. It also makes AI readiness testing structured for institutions (Zawacki-Richter et al., 2019). By translating leadership theory into observable actions, the technology helps schools voluntarily steer AI-GenAI use to complement educational values rather than dictate them.

6. Conclusions, limitations and future works

This study presents a reliable and valid instrument to measure educational leadership for AI-GenAI integration, operationalizing empowerment, orientation, and ethical stewardship. Grounded in current leadership theory, the tool bridges a key gap between conceptual models and practical demands for digital transformation in schools, going beyond generic technology leadership to address transformational, pedagogical, and ethical competencies. The instrument's psychometric robustness, confirmed through EFA, CFA, and multiple reliability indices, demonstrates that empowerment, orientation, caution and collaboration are distinct but interdependent dimensions, reflecting the multifaceted realities of educational leadership in digital contexts.

Despite the strong psychometric performance of the instrument, several limitations must be acknowledged. First, as the scale is based on teachers' self-reported perceptions, the results may be subject to biases such as social desirability or subjective interpretation of leadership behaviours. Second, although the sample size was adequate, its distribution was limited to teachers from Spain, which may restrict the generalizability of the findings to other cultural, organisational, or institutional contexts. Future research should therefore replicate the validation process in different countries, educational stages, and types of institutions to examine the instrument's cross-cultural stability. Moreover, although the overall sample was relatively large, future studies would benefit from even larger and more balanced samples, particularly ensuring sufficient representation across educational stages, gender groups and territorial contexts, to further strengthen the robustness and precision of multigroup analyses. Additionally, as the present study offers only a cross-sectional view of leadership in AI-GenAI integration, longitudinal studies are needed to evaluate the temporal stability of the scale and to understand how leadership perceptions evolve as schools progressively adopt AI-driven practices. Finally, further research should examine the instrument's applicability in real implementation contexts, for example, during the deployment of AI-related training programmes to determine its capacity to detect meaningful differences in leadership practices and its usefulness as a diagnostic tool in authentic educational settings.

The tool not only fills a methodological gap in the field of educational leadership and the use of AI-GEnAI tools, but also opens up new possibilities for research, diagnosis, and professional development, thus contributing to the construction of a transformative, ethical, and pedagogically sound digital culture in schools.

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