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Design and validation of a questionnaire on teachers' uses of generative artificial intelligence

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ABSTRACT

The use of generative artificial intelligence (GAI) in secondary education is transforming teaching practices and students' learning experiences. This study presents the design and validation of a questionnaire to assess the various educational uses of GAI by secondary school teachers. An initial pool of items was developed based on a comprehensive review of recent literature and validated through expert judgment. The preliminary version of the instrument was administered to a sample of 486 secondary school teachers in Spain. Confirmatory factor analyses supported a six-dimension structure: teacher management, creation of teaching materials, student assessment, student empowerment, attention to diversity, and student motivation. The questionnaire demonstrated high internal consistency and adequate convergent and discriminant validity. The results show that teachers use GAI both to optimize their professional performance and to enrich students' learning experiences. Practical implications of the instrument for teacher training, institutional decision-making, and future research directions are discussed.

1. Introduction

Artificial intelligence (AI) has become an established interdisciplinary field that integrates the design of algorithms and technologies aimed at replicating cognitive functions. Its ability to process large volumes of data and automate real-time decision-making makes it a cornerstone of technological innovation and one of the most influential forces shaping 21st-century transformation [1,2].

There is no single, universally accepted definition of AI, given the multiplicity of its characteristics and applications. Kaelbling and Moore [3] originally defined AI as the capacity of computational systems to adapt to dynamic environments, address highly complex problems, devise strategies, and perform tasks requiring advanced levels of intelligence. Later, Skilton and Hovsepian [4] redefined AI as a set of systems designed to process information and undertake tasks previously carried out by humans, thereby facilitating the progressive automation of cognitive functions.

The European Commission [5] proposed a general definition: "Artificial intelligence refers to systems that display intelligent behaviour by analysing their environment and taking actions – with some degree of autonomy – to achieve specific goals" (p. 1). A relevant study on the conceptual complexity of AI and its possible definitions and taxonomies is that of Samoili et al. [6]. The rapid and continuous evolution of AI also calls for a definition that takes into account the stages of its development: symbolic AI, data-based AI, and context-aware AI—each reflecting different levels of complexity and autonomy [7].

One of the most socially impactful and controversial applications of artificial intelligence is its ability to generate high-quality content that is nearly indistinguishable from that created by humans [8]. Generative Artificial Intelligence (GAI), through deep learning and the modelling of complex structures, goes beyond data analysis and the automation of routine tasks to enable the creation of innovative and context-sensitive content. The successful launch of ChatGPT has significantly increased public access to such tools, accelerating both interest in and debate about the uses of GAI [9].

Among its many applications, GAI's use in education is transforming

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not only general processes of educational management but also the very foundations of pedagogical thinking and instructional methodology. More broadly, it is reshaping the teaching–learning relationship by affecting cognitive, metacognitive, emotional, and social dimensions [10].

The emergence of ChatGPT, along with other similar GAI applications, has intensified the debate over its impact on education—particularly in relation to content production and student assessment. While some view it as a disruptive technology with the potential to transform educational processes, others see it as a threat that facilitates academic dishonesty and undermines the development of essential competencies [11].

The debate on the applications and implications of GAI in education is rapidly evolving. Nevertheless, existing studies often remain broad in their definitions and in their accounts of how teachers actually employ GAI in practice [12], while other research tends to focus on specific case studies or disciplinary contexts [13]. A clear gap can therefore be identified in the literature: the absence of validated instruments capable of systematically and reliably assessing educators' actual use of GAI, and of linking this use to teaching practices, pedagogical innovation, and student motivation.

2. Theoretical background

The potential of GAI has become evident across many areas of the educational landscape, continuing to transform both administrative and academic activities. This transformation opens up a wide range of opportunities for teachers by enhancing student autonomy through personalised learning. New forms of interaction and collaboration are also encouraging deeper reflection on ethical considerations and equity, potentially fostering more inclusive and socially aware education systems [14,15].

In secondary education, there has been consistent global growth in the use of GAI. Its application reflects the evolving models proposed by Ouyang and Jiao [16]: the three paradigms of use—AI-Directed (where the student is a recipient), AI-Supported (where the student collaborates), and AI-Empowered (where the student leads)—coexist within current secondary teaching and learning experiences. In general, GAI can be used by secondary teachers to automate tasks, deliver personalised feedback, and enhance their instructional approaches. According to the classification proposed by Martínez-Comesaña et al. [9], GAI use in secondary education can be grouped into three broad categories: administrative, instructional, and learning-focused.

With regard to the automation of administrative tasks in education, Guan et al. [17] examined the evolving role of AI in educational management. The automation of teachers' administrative workload has expanded in recent years, and the development of GAI can further relieve such burdens [18]. Beyond teacher-focused management, GAI impacts a wide range of administrative processes—for example, student enrolment or library services—and, more broadly, supports students in handling various academic tasks [19].

Studies have shown that excessive administrative workload constrains teachers' pedagogical practice. Chen and Zhao [20] reported that greater bureaucratic responsibilities reduce time for lesson preparation, marking and feedback, with negative effects on teaching quality. They also observed diminished student interaction and a reliance on more traditional, less participatory methods. This challenge could, however, be mitigated using AI to automate routine administrative tasks.

What has been defined as instructional uses refers to teachers' application of GAI to enhance their teaching practices, including tasks such as designing materials, creating learning activities, developing individualised content, and supporting assessment processes. The use of GAI for the creation of teaching materials and the design of learning activities in secondary education has been investigated across various contexts and disciplines (e.g., [21,22]). These studies report widespread benefits in multiple aspects of teaching, although they also highlight limitations and inaccuracies in GAI-generated content, as well as the need for adjustment and oversight by the human teacher [23].

The use of GAI to support the creation of teaching materials and activities is also justified by the growing diversity of secondary school students. Heterogeneous trajectories, interests and learning difficulties demand flexible and personalised approaches, with varied resources to promote meaningful learning [24]. In this context, GAI represents a strategic tool that enables teachers to design innovative and diversified activities more efficiently, fostering both deep learning and the development of key twenty-first-century competences [25].

Teachers often identify the field of assessment as one of the areas most positively affected by the use of GAI—both in terms of grading and test automation, and for predicting academic performance [9]. The application of GAI in assessment processes within secondary education raises at least two central issues. On the one hand, studies have examined the potential of GAI to generate automated assessment tools, saving teachers time and offering potential advantages in feedback provision [26,27]. In this regard, the capacity for immediate and personalised feedback has been emphasised by Tang et al. [28], who focused on the dialogic dimension of GAI. The meta-analysis by Wisniewski et al. [29] highlighted that elaborated feedback—containing explanations rather than merely the correct answer—is particularly effective in promoting higher-order learning tasks and deep information processing. To provide such high-quality feedback, teachers can draw on GAI to enrich and personalise recommendations, thereby supporting students in improving their learning [28]. On the other hand, the widespread use of GAI by both students and teachers has fuelled debates about the need to reconsider traditional forms of assessment, particularly in light of concerns about the originality and authenticity of AI-generated work [30,31].

The learning dimension encompasses broader aspects of GAI implementation that are transforming pedagogical methodologies and reshaping the roles of teachers and students within the teaching–learning process. This includes individualised student monitoring, inclusion and attention to diversity, and motivational factors. These variables represent fundamental pillars of inclusive secondary education as they foster both learning and equity [32]. Adaptive systems make it possible to tailor content and activities to students' individual characteristics, thereby enhancing motivation as well as academic achievement. The case study by Cohn et al. [33] focuses on the use of GAI for tracking student progress and supporting teachers in identifying and addressing students' difficulties when building computational models and solving problems.

With regard to personalised instruction, GAI allows for the generation of original content tailored to each student's needs, proficiency levels, and learning styles [34]. Personalisation processes become more agile and feasible even with limited resources, thereby increasing content accessibility and supporting attention to learner diversity [35]. In this respect, the implementation of GAI technologies is also proposed as a means of promoting educational inclusion. Through personalisation, GAI can enhance accessibility, address specific cognitive and emotional needs, and foster equity [36].

Proper use of GAI can also enhance student autonomy. Xie et al. [37] examined how the frequency of interaction with chatbots influences learner autonomy, depending on whether they are used for virtual companionship or knowledge acquisition. Students who leverage the potential of GAI tend to engage actively, applying critical thinking and creativity. Ali et al. [38] investigated the use of GAI in information management, concluding that secondary school students were able to critically identify and reflect on the impact of misinformation with the support of GAI tools. Similarly, Tang et al. [28] found evidence of active student participation in dialogues with GAI, including the use of follow-up questions that reflect critical thinking and creativity.

Furthermore, students are increasingly using GAI tools to ideate, structure, draft, and revise their written work [39]. The study by Labadze et al. [40] shows that students employ GAI as an interactive learning support for understanding content and resolving doubts. Finally, effective use of GAI has been shown to improve students' attention, confidence, and satisfaction [41]. A teaching style that supports student autonomy, combined with clear and structured guidance, creates an optimal learning environment in which students feel more competent, motivated and engaged. This combination is crucial as it meets learners' needs for both autonomy and competence [42].

The use of GAI can enhance student motivation [43]; these benefits were demonstrated by Meyer et al. [44] in an empirical study involving a sample of 459 students. However, the effects of GAI on motivation must be considered in relation to students' social connections and ethical concerns [45]. Motivation, and intrinsic motivation in particular, is consistently associated with higher academic achievement, greater task persistence, stronger emotional well-being and better school adjustment [46]. Shikun et al. [47] investigated the impact of chatbots on speaking skills among English as a Foreign Language (EFL) learners using both quantitative and qualitative methods, also reporting improvements in students' motivation and confidence. More broadly, Xiaoyu et al. [48] found that GAI acts as a catalyst for sparking students' interest and active engagement by creating a more accessible and less intimidating learning environment. This technology helps students approach complex tasks with reduced pressure, thereby promoting a more positive educational experience and greater enthusiasm for learning [49].

Students' perceptions of GAI in higher education have been examined on a large scale and from a comparative perspective by Ravšelj et al. [50], covering 109 countries. The findings of this study indicate that students regard GAI as particularly useful for brainstorming, summarising and information retrieval, and, more broadly, for simplifying complex tasks.

Despite these benefits, the variety of GAI applications and their potential consequences in education are perceived ambivalently by secondary school teachers. According to Delgado et al. [51], the main advantages identified by teachers relate to the creation of materials and learning activities. In contrast, concerns centre on the misuse of these tools by students, which may undermine essential skills at this educational stage—such as information literacy and the development of critical thinking. Similarly, ElSayary [52] found that teachers acknowledged significant benefits of ChatGPT in lesson planning and teaching activities, but perceived fewer advantages in areas such as assessment and feedback. Reported limitations include concerns about potential biases, the accuracy of information provided by GAI tools, and the lack of human interaction, which may reduce their effectiveness in educational contexts.

Other studies [53,18] have reached similar conclusions, recognising the pedagogical potential of GAI in secondary education. However, they emphasise the critical importance of teacher training and professional development to ensure effective use of these technologies.

Despite the growing interest in GAI within the field of education, there is currently a lack of validated instruments capable of systematically and reliably measuring how secondary school teachers are integrating these technologies into their practice. The absence of standardised tools limits both the rigorous evaluation of such practices and the development of evidence-based training initiatives and educational policies. In this context, there is a clear need to design specific instruments that can capture the diversity of ways in which teachers are incorporating GAI into their professional roles. A valid and reliable questionnaire would contribute to generating robust empirical evidence and guiding data-informed improvements in educational practice. Therefore, the aim of this study is to design and validate an instrument to identify the various ways in which secondary school teachers are using GAI in their teaching.

3. Method

This study adopted a quantitative methodological approach to collect numerical data, employing a survey-based design to develop a valid and reliable questionnaire. The quantitative method was specifically chosen for its capacity to measure a range of items and provide interpretations that are reliable, objective, and generalisable—essential qualities for validating an assessment instrument focused on teachers' use of GAI in secondary education [54].

A survey model, specifically a questionnaire, was used to collect data from a large sample of participants within a relatively short time frame. Survey research offers a straightforward means of gathering information from a target population, making it a suitable choice for this study as it enables a comprehensive understanding of the underlying reasons for GAI usage among secondary school teachers [55].

A cross-sectional research design was employed [56]. This approach was selected for its appropriateness in evaluating different dimensions of GAI use through statistical analysis, allowing for the identification of meaningful patterns relevant to the development of a valid and reliable assessment tool. The construction of the new instrument followed several essential steps, including the development of an initial item pool, expert review, a pilot study involving item refinement, and the validation of the final scale to confirm its psychometric robustness [57].

3.1. Participants

A non-probability purposive sampling method was employed, using incidental or convenience criteria to recruit secondary school teachers in Spain to complete the questionnaire [58]. The sample consisted of 486 Spanish teachers, of whom 45.47 % were male and 54.53 % were female. Participants' ages ranged from 20 to 30 years (11.73 %), 31 to 40 years (23.87 %), 41 to 50 years (34.78 %), 51 to 60 years (25.72 %), and over 60 years (3.9 %).

Regarding the disciplinary area of their university qualifications, 37.65 % held degrees in Arts and Humanities, 17.9 % in Sciences, 8.23 % in Health Sciences, 17.7 % in Social and Legal Sciences, and 18.52 % in Engineering and Architecture. As for teaching experience, 6.58 % had less than one year of experience, 50.41 % had between 1 and 10 years, 19.34 % had between 11 and 20 years, 17.28 % had between 21 and 30 years, 5.97 % had between 31 and 40 years, and 0.41 % had >40 years of experience.

We employed a convenience sampling approach, driven by institutional access, timetable constraints and ethical approvals required. This strategy is common in educational technology research where randomisation is infeasible. While efficient for recruiting naturally occurring cohorts, convenience sampling can introduce selection, coverage and self-selection biases. Consequently, statistical inferences are interpreted with caution and framed as context-bound evidence that is most directly applicable to institutions with similar profiles.

3.2. Procedure

The research project was submitted to the university's ethics committee and approved under registration code 2024–643. The item construction process involved experts in educational research methods, artificial intelligence, linguistics, and psychology.

A pilot study was conducted using an incidental sample of 52 teachers, which allowed for adjustments to the wording of certain items to improve clarity and comprehension. The final instrument consisted of 30 items designed to evaluate six dimensions of GAI use in teaching: Teacher Management, Creation of Teaching Materials, Student Assessment, Student Empowerment, Attention to Diversity, and Student Motivation. Each dimension was measured using five items (see Table 1). A 10-point Likert-type scale was used, ranging from 1 ("Never") to 10 ("Always").

Collaboration for data collection was requested from secondary schools across Spain using publicly available contact information found online. Teachers could access the questionnaire via a Microsoft Forms link, which first presented detailed information about the research

Table 1
GAI teaching use questionnaire in secondary education.

Concept	Meaning	Items
Teacher Management	Refers to the integration of GAI tools into teachers' administrative and organisational tasks, aiming to optimise planning, documentation and the efficiency of everyday teaching management.	1. I use GAI tools to draft my teaching programmes based on the ideas I provide. 2. I use GAI to plan course content more effectively. 3. I use GAI to generate administrative documents related to my lesson planning (timetables, group creation, material lists, assessment calendars, etc.). 4. I use GAI to create diagrams, tables, figures, and presentations with student data for school meetings. 5. I use GAI to save time in my daily teaching management.
Creation of Teaching Materials	Refers to the use of GAI to design and produce adapted, innovative, and functional educational resources that support teaching and enhance student understanding.	6. GAI enables me to create personalised teaching materials for my students. 7. I use GAI to generate innovative and engaging educational content. 8. GAI helps me develop materials that support students' understanding. 9. I use GAI to generate examples and practical cases relevant to my classes. 10. I use GAI to create teaching materials that complement my explanations.
Student Assessment	Involves the use of GAI to design, enhance and streamline assessment processes, from creating tools to providing feedback, promoting more efficient and personalised evaluation.	11. GAI enables me to create personalised assessments for each student. 12. I use GAI to design different types of assessment tools. 13. I use GAI to improve my assessment tools. 14. GAI facilitates me the review and correction of tests. 15. I use GAI to generate immediate feedback on assessments.
Student Empowerment	Involves teaching and promoting ethical, critical, and autonomous use of GAI by students as a tool to support their learning, decision-making, and study management.	16. I teach students to use GAI ethically. 17. I train students to critically evaluate information generated by GAI. 18. I provide tools and strategies for students to use GAI in their studies (information search, solving doubts, self-correction, etc.). 19. I teach students to integrate GAI into their learning processes (summarising, creating mind maps, generating conceptual diagrams, etc.). 20. I teach students to use GAI to manage their study time more efficiently.
Attention to Diversity	Refers to the use of GAI to adapt content, activities, and teaching strategies that respond to the specific needs of students, promoting inclusive and equitable teaching.	21. I use GAI to personalise educational content for students with specific educational support needs. 22. I use GAI to adapt activities to students' needs. 23. I use GAI to get suggestions on inclusive teaching strategies based on student profiles. 24. GAI helps me implement strategies that respond to student diversity and promote active class participation. 25. I use GAI to design assessments for students with specific educational support needs.
Student Motivation	Describes GAI's capacity to increase students' interest, curiosity, and engagement with school content and activities, contributing to a more engaging learning environment.	26. The use of GAI in my classes increases students' interest in the topics covered. 27. When I use GAI in class, students' curiosity increases. 28. I use GAI in class to boost students' interest in achieving good grades. 29. The application of GAI leads to greater student involvement in learning the subject content. 30. Using GAI in my classes makes students enjoy the subject more.

project, followed by an informed consent form, and finally the questionnaire itself. Responses were gathered between July and December 2024.

To ensure the quality of the data collected, consistency checks were implemented. In particular, the presence of unusual response patterns—such as selecting the same option across all items (straight-lining)—was monitored, and response times were reviewed. Voluntary participation was encouraged through a formal institutional invitation, highlighting the academic relevance of the study and assuring participants of the confidentiality of their responses. Additionally, the questionnaire was designed to be concise and easy to understand, thereby minimising participant fatigue and enhancing the overall quality of the responses.

3.3. Data analysis

Data analysis was carried out using a range of statistical procedures. Procedures typically associated with item analysis were implemented, including the calculation of descriptive statistics. Reliability was assessed using Cronbach's alpha coefficient. Construct validity was examined through confirmatory factor analysis (CFA), applying the maximum likelihood (ML) method, as the item distributions met the criteria for normality.

Discriminant validity was assessed in two ways. First, inter-factor correlations were calculated using Pearson's correlation coefficient. Second, the squared correlations (r^2) between factors were computed and compared against the average variance extracted (AVE) for each factor, with the expectation that r^2 values would be lower than the corresponding AVE values.

Convergent validity was evaluated using the AVE, which represents the proportion of variance explained by each factor in the scale. In addition, composite reliability (CR) was also reported. All statistical analyses were conducted using IBM SPSS Statistics version 29 and JASP version 0.19.

4. Results

4.1. Data cleaning and preparation

The initial step in analysing the dataset involved cleaning and preparing the data. During this phase, the straight lining method was applied to detect any unusual or inconsistent responses [59]. This process did not reveal any major issues.

The dataset was further explored using minimum and maximum values, means, and standard deviation, and its distribution was examined through checking univariate skewness and kurtosis. To evaluate the distribution of the data, the guidelines proposed by Curran et al. [60] were followed. According to these criteria, skewness values between −2 and +2, and kurtosis values between −7 and +7, are unlikely to negatively impact further analyses. In this study, item skewness values ranged from −1.07 to 0.17, while kurtosis values fell between 0.58 and 0.78, indicating that all items exhibited an acceptably symmetrical and mesokurtic distribution. These results support the use of the ML method for the subsequent CFA.

In addition, the R^2 value for each item was reported, indicating the proportion of variance in the item explained by its corresponding latent factor. All R^2 values exceeded 0.50, which is considered the threshold for acceptable explanatory power [61]. All standardised factor loadings were statistically significant ($p < .001$), indicating a strong relationship between each item and its associated factor. Furthermore, the loadings were consistently high, ranging from 0.76 to 0.96, well above the recommended minimum value of 0.50 for substantial item-factor association [62]. These results demonstrate that the items load appropriately onto the proposed theoretical dimensions and provide strong support for the structural validity of the model. The results of these analyses are presented in Table 2.

4.2. Reliability

The internal consistency of the instrument, assessed using Cronbach's alpha, yielded a value of $\alpha = 0.92$ for the overall scale. For each of the six subscales, the Cronbach's alpha coefficients were as follows: GAI use for Teacher Management ($\alpha = 0.91$), Creation of Teaching Materials ($\alpha = 0.92$), Student Assessment ($\alpha = 0.90$), Student Empowerment ($\alpha = 0.89$), Attention to Diversity ($\alpha = 0.86$), and Student Motivation ($\alpha = 0.90$). No items were identified whose removal would improve the reliability of the corresponding subscales.

4.3. Content validity

Content validity of the questionnaire was assessed through an expert judgement procedure. The evaluation was carried out by six experts with extensive experience and knowledge in educational research methodology. All six were university lecturers, and four of them had also taught at the secondary education level. They were asked to quantitatively assess a total of 60 items in terms of three criteria: clarity (the degree to which items were comprehensible), relevance (the degree to which items aligned with the intended construct), and pertinence (the degree of correspondence between item content and the theoretical dimension it was intended to measure).

A five-point scale was used for these ratings, with scores ranging from 1 (not at all clear/relevant/pertinent) to 5 (very clear/relevant/pertinent). Additionally, the experts were invited to provide qualitative feedback on each item. The initial bank of 60 items had been developed based on a review of recent scientific literature on GAI in educational contexts, along with an analysis of prior teaching experiences in secondary education.

For the expert judgement process, individual aggregation of evaluations was selected [63], as this approach minimises potential social influence among evaluators and promotes more objective and independent assessments. To analyse inter-rater agreement, Aiken's V coefficient was calculated, with values exceeding 0.80 for most items, indicating a high level of expert agreement and strong content validity. Only items that obtained a V value of ≥ 0.78 and a mean rating of 4.8 or higher across all three criteria (clarity, relevance, and pertinence) were retained. This process led to the elimination of redundant items or those with lower theoretical or linguistic adequacy, resulting in a final version

Table 2
Descriptive statistics for the questionnaire items.

Item	Min.	Max.	Mean	SD	Skewness	Kurtosis	R^2	Std. estimate	Std. error	95 % CI - Lower	95 % CI - Upper
TM1	1	10	3.63	3	.67	−1.07	.72	.85	.03	.8	.89
TM2	1	10	3.61	2.97	.69	−1.02	.78	.88	.02	.84	.91
TM3	1	10	2.96	2.75	1.22	.17	.58	.76	.03	.7	.82
TM4	1	10	3.04	2.77	1.11	−0.16	.60	.77	.03	.72	.82
TM5	1	10	4.17	3.18	.45	−1.32	.92	.96	.03	.89	1.02
CTM6	1	10	4.92	3.18	.08	−1.46	.84	.92	.01	.88	.94
CTM7	1	10	4.65	3.15	.15	−1.49	.90	.95	.01	.93	.96
CTM8	1	10	4.8	3.13	.07	−1.47	.93	.96	.01	.95	.97
CTM9	1	10	4.77	3.32	.17	−1.52	.88	.94	.01	.91	.95
CTM10	1	10	4.7	3.26	.18	−1.5	.86	.93	.01	.9	.94
SA11	1	10	3.36	2.84	.87	−0.6	.71	.85	.03	.79	.89
SA12	1	10	3.94	3.06	.52	−1.2	.78	.89	.02	.85	.91
SA13	1	10	4.03	3.17	.47	−1.32	.78	.88	.02	.85	.91
SA14	1	10	3.01	2.68	1.11	−0.04	.57	.76	.03	.7	.81
SA15	1	10	2.67	2.55	1.44	.92	.55	.75	.03	.68	.8
SE16	1	10	4.33	3.19	.38	−1.3	.73	.85	.02	.8	.9
SE17	1	10	4.35	3.14	.37	−1.26	.68	.82	.03	.77	.87
SE18	1	10	4.02	3.08	.47	−1.24	.89	.95	.01	.92	.97
SE19	1	10	3.66	2.96	.69	−0.87	.84	.92	.02	.88	.94
SE20	1	10	3.05	2.76	1.11	−0.04	.66	.81	.03	.76	.86
AD21	1	10	3.57	3	.74	−0.89	.82	.91	.02	.87	.93
AD22	1	10	3.81	3.05	.59	−1.11	.85	.92	.02	.89	.95
AD23	1	10	3.56	3.07	.75	−0.98	.83	.91	.02	.87	.94
AD24	1	10	3.5	2.97	.77	−0.86	.87	.93	.02	.9	.96
AD25	1	10	3.17	2.86	1.01	−0.38	.82	.91	.02	.87	.93
SM26	1	10	3.89	2.92	.52	−1.09	.91	.95	.01	.92	.98
SM27	1	10	3.95	2.99	.47	−1.19	.92	.96	.01	.94	.97
SM28	1	10	3.5	2.86	.7	−0.91	.90	.95	.01	.92	.97
SM29	1	10	3.69	1.83	.6	−0.95	.86	.93	.01	.91	.95
SM30	1	10	3.71	2.91	.61	−1.01	.88	.94	.01	.91	.96

comprising 30 items, distributed across six dimensions that reflect the various ways in which GAI is used in secondary education teaching.

4.4. Construct validity

The results were found to align with the proposed theoretical model, using the criteria established by Byrne [64] and Hu and Bentler [65]. Table 3 presents both the obtained and reference values for model fit, based on the following statistics: Chi-square (χ^2), Goodness of Fit Index (GFI), Normed Fit Index (NFI), Parsimonious Normed Fit Index (PNFI), Root Mean Square Error of Approximation (RMSEA), Comparative Fit Index (CFI), Tucker-Lewis Index (TLI), Incremental Fit Index (IFI), Relative Fit Index (RFI), and Standardised Root Mean Square Residual (SRMR).

The model fit indices indicated a good fit for the proposed model [66]. The only exception was the Chi-square statistic, which yielded an unsatisfactory value. However, this index is known to be extremely sensitive to sample size, with larger samples typically resulting in poorer Chi-square values. Overall, the results support the consistency and adequacy of the proposed theoretical model. Even though the χ^2 statistic yielded a significant value suggesting an apparently unsatisfactory fit, this outcome was to be expected given the large sample size. The literature recognises that the chi-square test is highly sensitive to sample size, often flagging trivial discrepancies as poor fit when *N* is very large [67]. Indeed, with samples exceeding approximately 400 cases, the χ^2 test tends to reject even well-specified models [68]. Consequently, methodological guidance recommends evaluating model fit using multiple indices in combination rather than relying exclusively on χ^2 [67]. In our analysis, both comparative and absolute indices consistently indicate good model fit: for example, the obtained CFI and TLI exceed the 0.95 threshold, while the RMSEA is well below 0.08—values that denote excellent fit according to conventional criteria. Taken together, these favourable indices support acceptance of the proposed model.

4.5. Convergent validity

Convergent validity of the instrument was assessed by calculating the Average Variance Extracted (AVE) and Composite Reliability (CR) for each of the six factors. As shown in Table 4, all AVE values exceeded the recommended threshold of 0.50, ranging from 0.70 to 0.90. The lowest observed value corresponded to the Student Assessment factor (AVE = 0.70), indicating that even in the most conservative case, the construct accounted for at least 70 % of the variance in its items—strong evidence of convergent validity [59]. Similarly, CR values ranged from 0.92 to 0.98, far surpassing the minimum acceptable level of 0.70, confirming a high degree of internal consistency for each dimension [59].

4.6. Discriminant validity

Pearson correlations were calculated between the observed factors (see Table 5). For the factors to be considered related yet sufficiently distinct, they are expected to be significantly correlated, but not beyond a moderate level—specifically, with correlation coefficients below 0.70 [69].

Furthermore, as shown in Table 6, the AVE for each construct was greater than the squared correlation between that construct and any of the other factors, indicating adequate discriminant validity [70].

Based on these results, it can be concluded that the dimensions “teacher management”, “creation of teaching materials”, “student assessment”, “student empowerment”, “attention to diversity”, and “student motivation” represent distinct factors that can be jointly used to measure teachers’ use of GAI in secondary education.

Table 3
Model fit index.

Index	Result	Fit criterion
χ^2	.000	p>.05
GFI	.914	p>.90
NFI	.944	p>.90
PNFI	.79	p>.90
RMSEA	.045	p<.05
CFI	.963	p>.90
TLI	.955	p>.90
IFI	.96	p>.90
RFI	.934	p>.90
SRMR	.04	p<.05

Table 4
Assessment of convergent.

Factors	AVE	CR
Teacher management	.73	.97
Creation of teaching materials	.88	.98
Student assessment	.70	.93
Student empowerment	.76	.95
Attention to diversity	.84	.97
Student motivation	.90	.92

Table 5
Correlation between questionnaire factors.

Factors	1	2	3	4	5	6
1. Teacher management		.61**	.62**	.54**	.52**	.57**
2. Creation of teaching materials			.64**	.61**	.66**	.66**
3. Student assessment				.59**	.58**	.52**
4. Student empowerment					.61**	.67**
5. Attention to diversity						.54**
6. Student motivation						

Note. ** = $p < .001$.

5. Discussion

The present study successfully designed and validated a questionnaire to assess secondary school teachers’ use of generative artificial intelligence (GAI), thereby achieving its original objective. The findings confirm the proposed multidimensional structure and demonstrate strong psychometric properties for the instrument. Specifically, the final scale consists of six distinct dimensions—teacher management, creation of teaching materials, student assessment, student empowerment, attention to diversity, and student motivation—and exhibits high internal reliability.

Internal consistency analysis yielded outstanding results, with all values well above the recommended threshold of 0.70 for newly developed instruments [59,57], indicating strong reliability for both the overall scale and each of its subscales. Moreover, no item showed a significant improvement in reliability if removed, reinforcing the internal coherence of the retained items, as similarly noted in previous scale development studies [66].

From a structural perspective, the CFA supported the validity of the proposed six-factor model, which was grounded in both the conceptual framework and a thorough review of literature on GAI usage in education [9,16]. All standardised factor loadings were high (ranging from

Table 6
Squared correlations (r^2) between factors.

Factors	1	2	3	4	5	6
1. Teacher management		.37	.38	.29	.27	.32
2. Creation of teaching materials			.41	.37	.44	.44
3. Student assessment				.35	.34	.27
4. Student empowerment					.37	.45
5. Attention to diversity						.29
6. Student motivation						

0.76 to 0.96) and statistically significant, providing empirical support for the relationship between the items and their respective theoretical constructs. Inter-factor correlations fell within a moderate range, indicating that the dimensions are related yet clearly represent distinct aspects of GAI use in teaching [22].

With regard to convergent validity, the results showed highly favourable values for both AVE and CR. These findings indicate that each dimension of the questionnaire explains a substantial proportion of the variance in its respective items, in line with the stringent criteria established by Fornell and Larcker [70] and reinforced in recent studies [59,61]. The high CR values further demonstrate that the items within each subscale share a large proportion of common variance—an indicator of internal consistency that complements Cronbach's alpha and is particularly relevant in structural equation models [62].

Discriminant validity was also confirmed using Fornell and Larcker's [70] criterion. In all cases, the AVE for each factor exceeded the squared correlation between that factor and any other, indicating that each dimension captures unique aspects of the broader construct and does not overlap excessively with the others. This criterion offers robust evidence that the questionnaire dimensions are sufficiently distinct. Moreover, the observed inter-factor correlations did not exceed critical thresholds for lack of discriminance, further strengthening this conclusion [66].

From a theoretical perspective, the six-factor structure offers a nuanced view of how teachers are using GAI in practice. While it aligns partially with previous classifications, it provides a more fine-grained distinction. Martínez-Comesaña et al. [9] proposed three overarching categories for GAI use in secondary education—administrative, instructional, and learning-related—but our findings suggest that teachers differentiate more specific subdimensions within those categories. For instance, in the instructional domain, the creation of teaching materials and student assessment clearly emerge as distinct uses, whereas in the learning domain, several student-related components (empowerment, attention to diversity, and motivation) are differentiated.

This disaggregation into six factors reveals that teachers view GAI as a versatile tool that serves both to support their own professional tasks (e.g., managing administrative duties, generating teaching resources, and conducting assessment) and to enhance students' learning experiences (e.g., through personalisation, increased motivation, and the promotion of student autonomy). Overall, this multidimensional structure supports the coexistence of different paradigms for integrating AI in education, as described by Ouyang and Jiao [16], in which GAI functions either as an assistant to the teacher (AI-Supported) or as a driver of enriched, student-centred learning experiences (AI-Empowered).

When interpreting each dimension, a clear alignment is observed with findings from previous studies and with the pedagogical potential of GAI described in the literature. The dimension of Teacher Management confirms that teachers are using GAI to automate administrative and planning tasks, which aligns with research reporting that AI can alleviate bureaucratic and managerial workload in educational institutions [17,18]. Similarly, the Creation of Teaching Materials dimension reflects the widespread use of generative tools to develop educational content and activities. This is consistent with earlier evidence that GAI (e.g., models such as ChatGPT) can support the creation of creative and personalised teaching resources, thereby enhancing instructional design efficiency [21,22].

The inclusion of Student Assessment as a distinct dimension suggests that teachers are increasingly relying on GAI to support assessment processes, such as test generation, automated marking, or personalised feedback. This emerging trend has been highlighted in recent studies exploring the integration of AI in assessment practices [26] and is also discussed in the field of educational assessment [30], where the scope and quality assurance of AI-based assessment systems remain a topic of debate.

Regarding student-centred dimensions, this study confirms the relevance of GAI in enriching the learning experience. The Attention to Diversity dimension indicates that teachers view GAI as a valuable ally in adapting instruction to students' diverse needs, learning rhythms, and interests—facilitating more inclusive teaching approaches. This aligns with research that underscores AI's potential to personalise learning and promote equity in the classroom ([14]; Delgado de Frutos et al., 2024; [15]).

Likewise, the Student Motivation dimension shows that teachers recognise GAI as a tool for increasing student engagement and motivation, whether through more dynamic activities, novel content, or gamified AI-assisted learning environments. This finding is in line with studies documenting positive effects of AI on students' motivation and participation [45,43].

Finally, the Student Empowerment dimension suggests that teachers value the role of GAI in giving learners greater autonomy and a more active role in their learning processes. The literature proposes that GAI can transform students into creators and active agents within AI-supported educational environments [38], for example, through the generation of ideas, solutions, or content by students themselves with the support of such tools. Our findings confirm that this vision is beginning to take root in teaching practice: teachers are using AI not only to enhance instruction but also to foster students' capabilities, in line with a pedagogical model in which AI amplifies the possibilities for personalised and creative learning.

Despite its contributions, this study presents several limitations that should be acknowledged. First, the sample was limited to secondary school teachers in Spain, selected through convenience sampling. Potential biases include over-representation of institutions with greater openness to innovation, differential participation by more motivated teachers, and contextual features (e.g., digital infrastructure, instructional culture) that may not mirror those of other settings. The sample may over-represent settings that were available and willing to participate during the data-collection window, and the findings are most applicable to secondary schools with similar organisational and demographic profiles. As such, the results and the validity of the questionnaire are restricted to this specific educational and geographical context. It would be inappropriate to generalise the findings to teachers in other countries or educational levels without further cross-cultural validation studies. Second, the questionnaire relies on self-reported GAI use, which may be subject to social desirability bias and therefore may not capture actual classroom practices or the effectiveness of such uses. As with any self-report instrument, responses may also be affected by reference-frame effects when judging engagement with generative AI tools. In classroom contexts, teachers may under- or over-report actual usage depending on perceived norms, institutional policies, or assessment stakes. Moreover, item interpretation can vary with AI literacy, leading to heterogeneous thresholds for what counts as "using" or "relying on" an AI application. These aspects could be explored in future research through qualitative methodologies that complement the information gathered with this questionnaire.

Moreover, given the rapid development of GAI technologies, it is likely that new educational applications will emerge that were not covered by the original instrument. This implies that the questionnaire may require regular updates to maintain its relevance and coverage as the landscape of AI in education continues to evolve. Finally, this study focused on the psychometric validation of the instrument and did not delve into analyses of teachers' experiences with GAI, nor into the relationship between these uses and educational outcomes such as academic performance or student engagement. These limitations point to several promising avenues for future research.

In this regard, a number of future research directions are proposed. First, it would be valuable to replicate the questionnaire validation in other international contexts and across different educational stages (e.g., early childhood, primary, and higher education) to assess factorial invariance and the relevance of the six dimensions among diverse teaching populations [71]. Second, future studies could examine correlates and outcomes associated with GAI use in teaching—for example, whether increased use of certain dimensions (such as personalisation or AI-assisted assessment) is linked to improvements in student motivation, teacher satisfaction, or academic achievement.

Longitudinal studies would also be useful for observing how GAI integration evolves in teaching practice over time, especially as teachers gain more training and AI tools become more accessible. Another research avenue could involve combining this instrument with others that assess teachers' attitudes, barriers, or competencies related to AI, in order to obtain a more comprehensive picture of teachers' readiness to incorporate AI into their instructional practices. In this regard, qualitative or mixed-methods approaches could both strengthen and extend the overall findings of this research, while also allowing for a more fine-grained examination of specific proposed dimensions. Case-based studies, in particular, can yield a deeper understanding of teachers' practical experiences [72,73].

Finally, given the dynamic nature of GAI, future research should investigate the effectiveness of training interventions focused on the six identified areas. For instance, experimental studies could evaluate whether targeted workshops on using GAI for instructional material development or for supporting diverse learners lead to increased frequency and quality of GAI adoption among teachers. These future investigations will complement and enrich the findings presented here, contributing to the consolidation of a robust body of knowledge to guide the responsible and effective integration of generative artificial intelligence in education.

6. Conclusions

This study presents the design and validation of a new questionnaire that enables the systematic assessment of teachers' use of generative artificial intelligence (GAI) in secondary education. The final instrument, comprising 30 items grouped into six dimensions, demonstrated high levels of validity and reliability, meeting established methodological standards for use in both educational research and applied contexts. The analyses confirmed that the six identified dimensions—teacher management, creation of teaching materials, student assessment, student empowerment, attention to diversity, and student motivation—are distinct yet complementary constructs that collectively capture the main ways in which secondary school teachers are incorporating GAI into their professional practice.

The main findings indicate that teachers surveyed are already using GAI tools for a variety of purposes. On the one hand, they use GAI to optimise their teaching practice by automating administrative and managerial tasks, generating personalised instructional materials, and supporting student assessment and feedback. On the other hand, they use GAI to enrich students' learning experiences, adapting instruction to individual needs (e.g., different learning paces or styles), enhancing motivation through innovative activities, and promoting greater autonomy and active engagement in the learning process.

This dual use—both to support teachers' professional tasks and to enhance students' experiences—suggests that GAI is being broadly integrated into secondary education. It is transforming everyday pedagogical tasks and classroom dynamics alike, contributing to more personalised, interactive, and inclusive approaches to teaching and learning.

Building on our validated six-dimension framework (teacher management, creation of teaching materials, student assessment, student empowerment, attention to diversity, and student motivation), we propose using the questionnaire as a diagnostic baseline and follow-up measure to locate dimension-specific strengths and gaps at teacher, departmental and institutional levels, and to align professional development and resource allocation accordingly.

Concretely, results pointing to low use of student assessment applications should inform the adoption of AI-aware assessment practices (e.g., clearly articulated rubrics that require process evidence such as drafts and rationale statements, systematic verification of AI-generated feedback, and version control to ensure traceability). Where creation of teaching materials scores is weaker, departments should curate discipline-appropriate prompt repositories and quality-assurance checklists covering factual accuracy, citations, licensing and bias, while establishing lightweight workflows for co-design and periodic auditing of AI-assisted resources. Findings related to teacher management should guide the formalisation of planning and documentation workflows supported by GAI, accompanied by clear governance on privacy, attribution and model transparency.

If student empowerment emerges as underdeveloped, teachers should embed metacognitive activities that make AI use explicit (declarations of use, reflection on when and how AI adds value, and comparison of AI and human outputs) to cultivate critical AI literacy. Lower scores in attention to diversity warrant structured use of GAI for accessibility and personalisation (linguistic simplification, multimodal formats, scaffolded variants) subject to equity and bias checks, while limited student motivation suggests integrating authentic scenarios and iterative, low-stakes inquiry tasks in which GAI supports exploration and formative guidance.

At the institutional and policy levels, aggregated results should inform a governance framework for responsible classroom AI (acceptable-use policies, data-protection standards, procurement criteria addressing accessibility and bias documentation) and targeted resourcing (infrastructure, mentoring and exemplars) to support those dimensions identified as less developed. Collectively, these actions translate questionnaire evidence into specific, scalable improvements in teacher learning, classroom practice and organisational decision-making across the six domains.

This research contributes a rigorous tool and a body of empirical evidence at a critical juncture in educational innovation. The emergence of GAI models has generated both anticipation and debate in the education sector, and our findings offer clarity and guidance: they identify concrete ways in which teachers are using these tools and validate those categories of use. The practical applications of GAI in secondary education—as revealed by our instrument—range from greater efficiency and personalisation in teaching to the empowerment of students in their own learning processes. Fully harnessing these potential benefits will require continued research and sustained support for teachers throughout this digital transformation. We hope that the questionnaire developed through this study will serve as a catalyst for further research and for the design of training initiatives that, ultimately, contribute to a more effective and evidence-based integration of generative artificial intelligence in secondary classrooms—for the benefit of both educators and students.

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CRediT authorship contribution statement

Héctor Pérez-Montesdeoca: Writing – review & editing, Writing – original draft, Methodology, Investigation, Data curation. **Daniel Rodríguez-Rodríguez:** Writing – review & editing, Writing – original draft, Methodology, Formal analysis. **David Stendardi:** Writing – review & editing, Writing – original draft, Investigation, Conceptualization. **Aitana Fernández-Sogorb:** Writing – review & editing, Writing – original draft, Methodology.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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