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Academic Integrity in Teacher Education in the GenAI Era: Academic Coordinators' Perspectives in Spain

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Abstract. This study explores academic dishonesty in pre-service teacher training programmes from the perspective of academic managers in Spanish universities. Using a quantitative design, based on an online questionnaire and a sample of 198 academic coordinators, it examines perceptions of the prevalence, evolution, and severity of 28 dishonest behaviours, including those involving generative artificial intelligence (GenAI). Results reveal that GenAI-related misconduct is perceived as particularly severe and rapidly increasing, though traditional forms such as plagiarism and contract cheating remain common. Significant differences in perception were found across variables such as age, institutional type, and years of management experience. A composite index (DB-PES) was developed to categorise behaviours by perceived urgency. Findings suggest that academic dishonesty is a dynamic phenomenon requiring systemic and pedagogically grounded responses. Institutions must prioritise ethical training, develop clear policies on AI use, and adopt flexible, responsive mechanisms to address evolving examples of misconduct. This study offers new insights to guide integrity strategies in teacher education.

Keywords: teacher training; academic misconduct; generative artificial intelligence; higher education ethics; educational leadership

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1. Introduction

Although academic integrity in pre-service teacher education has long been centred on plagiarism, it now confronts a rapidly shifting landscape of GenAI-enabled authorship and assessment that tests how universities safeguard the formation of future teachers. Academic ethics denotes a commitment to a defined set of ethical principles and responsible behaviours that are expected within the scholarly community (Tauginiene et al., 2018). It constitutes the ethical core that informs and sustains the practices of teaching, learning, research, and academic service (Sureda-Negre et al., 2016).

From this standpoint, integrity should be understood as a deliberate and ongoing commitment, which Killinger (2010) characterises as a personal choice to consistently maintain moral and ethical standards in academic contexts. The importance of academic integrity lies in its foundational role in building trust and ensuring the validity of academic outcomes. Without it, educational qualifications lose meaning, scholarly knowledge becomes unreliable, and public confidence in education erodes (Comas-Forgas et al., 2023).

For pre-service teachers and future educators, the cultivation of academic integrity is not merely a personal responsibility but a professional imperative (Bjelobaba & Cronqvist, 2022; Eaton & Khan, 2022). As a foundational principle of higher education, academic integrity fosters not only the acquisition of knowledge and skills but also an ethical disposition that is essential for professional practice (Guerrero-Dib et al., 2020). In the context of teacher education, this is especially critical, as students are expected to develop both pedagogical competence and moral accountability (Liu et al., 2016). Therefore, pre-service teachers must be prepared not only to impart knowledge and foster skills but also to model and promote core values such as honesty, fairness, and responsibility (Gottardello & Karabag, 2020).

Despite its centrality, academic integrity remains a fragile construct in teacher education. Research consistently reports widespread instances of plagiarism, contract cheating, and other forms of academic misconduct among pre-service teachers (Merkel, 2021; Newton & Essex, 2023). Indeed, DiPaulo (2022) revealed that more than 80% of pre-service teachers admitted to engaging in academically dishonest behaviours, with a significant portion involving serious violations such as copying and cheating in assessments. Not only is this trend worrying for ethical reasons but also with regard to the long-term impact on the professional standards of educational institutions.

Scholars have identified a complex collection of factors contributing to academic dishonesty, ranging from individual-level stress and lack of skills (Fontaine et al., 2020) to systemic gaps in ethical education and assessment design (Liu et al., 2016). For instance, Ransome and Newton (2018) demonstrated that many academic textbooks that are used to train university educators scarcely address integrity as a pedagogical objective, suggesting a systemic neglect that reinforces ignorance or apathy towards these issues. At the same time, the inconsistency between the ideal and actual roles played by university professors in promoting integrity further exacerbates the issue (Gottardello & Karabag, 2020).

A crucial issue is that ethical behaviour is not simply the product of rules but also of cultural and educational conditioning. Eaton and Khan (2022) argue that ethical habits begin early in life and must be intentionally developed through explicit instruction and daily modelling. Without sustained, embedded instruction, future educators may lack the competence or confidence to address academic integrity with their own students. Furthermore, Vučković et al. (2020) emphasise that many students and faculty do not have a clear understanding of ethical misconduct, pointing to a shared responsibility in fostering academic culture.

Recently, the challenge of cultivating academic integrity has been radically transformed by the emergence of generative artificial intelligence (GenAI) tools (Adiyono et al., 2025). Applications such as ChatGPT, Claude, and other large language models (LLMs) are being used increasingly—and sometimes surreptitiously—by students to complete writing tasks (Eaton, 2024; Lopes et al., 2024). Such technologies blur the boundaries between original authorship and co-creation with machines, raising urgent questions about how academic integrity should be reconceptualised in the digital age (Gallent-Torres et al., 2023).

In particular, pre-service teachers are impacted by these developments, although Su et al. (2025) found that pre-service teachers often exhibit ambivalence towards AI. While many recognise its potential to support learning, they also express concerns regarding its ethical implications and the possibility of dependency or misuse. The study by Markos et al. (2024) further illustrates this dual perspective: although exposure to ChatGPT increased participants' familiarity and reduced anxiety, few reported readiness to integrate AI tools into their future classrooms.

Thus, these findings reveal a crucial gap between technological adoption and ethical preparedness. As Eaton (2024) aptly argues, the current moment is one of post-plagiarism, whereby traditional definitions of misconduct no longer capture the realities of digital authorship. In such a world, the emphasis must shift from punitive models to proactive pedagogies that prepare pre-service teachers to critically engage with GenAI, develop AI literacy, and model ethical behaviours for their students.

A general approach to academic integrity in teacher education is urgently needed. Khan et al. (2020) and Bjelobaba (2020) advocate for embedding integrity into the curriculum through preventive pedagogical practices, such as constructive alignment, values-based instruction, and active learning methods. Instead of focusing solely on what not to do (i.e. cheating, plagiarism, collusion), academic integrity should be framed as a set of positive values (honesty, courage, responsibility) cultivated through consistent engagement.

Incorporating academic integrity across the curriculum also demands professional development for teacher educators themselves. As Bjelobaba and Cronqvist (2022) argue, pre-service teacher programmes must not only attend to student integrity but also prepare future teachers to teach integrity to children and adolescents. Yet this context (enabling pre-service teachers to teach ethics) is often overlooked, resting on the flawed assumption that ethical modelling occurs naturally through professional training. Consequently, more systematic instruction, combined with reflection on ethical dilemmas, is needed to prepare pre-service teachers to act and teach with integrity (Campbell, 2008).

The growing concern surrounding academic dishonesty in the context of teacher training programmes has prompted numerous investigations into students' behaviours and institutional responses (Vallespir-Adillón et al., 2024). However, relatively limited attention has yet been paid to the perceptions of academic managers, whose strategic and pedagogical roles place them at the forefront of the decision-making processes concerning academic integrity. Therefore, this study seeks to address this gap by focusing on the perspectives of academic managers in pre-service teacher training programmes (PTTPs) across Spanish universities.

Spain constitutes a theoretically and practically salient context through which to examine academic integrity in teacher education because it combines a documented baseline of academic dishonesty in higher education, mature integrity policies, and rapid, policy-driven digital and AI uptake in teacher preparation. Early national evidence showed the substantial prevalence of plagiarism among Spanish undergraduates, offering a pre-GenAI benchmark for integrity risks (Comas-Forgas et al., 2010). In parallel, Spanish universities have formalised integrity responses—codes, plagiarism-detection tools, and training—with documented differences between public and private institutions, underlining the need to understand managerial perspectives shaping implementation (Cerdà-Navarro et al., 2022).

At the teacher education level, Spain has prioritised digital competence via frameworks that are aligned with DigCompEdu and the national INTEF adaptation, which heighten the salience of integrity in technology-rich assessment (Cabero-Almenara et al., 2020). Recent large-sample studies also report widespread student use and acceptance of ChatGPT, bringing both benefits and ethical concerns—precisely the configuration that challenges integrity policies in teacher education (García-Alonso et al., 2024; Morell-Mengual et al., 2025). At the same time, Spanish pre-service teachers are highlighting the ongoing need to strengthen digital competences, reinforcing the timeliness of the present focus (Alonso García et al., 2024).

Building on previous work and employing a comprehensive quantitative approach, this research was designed to examine not only the perceived frequency, evolution and severity of dishonest academic behaviours, but also to determine how these perceptions may vary across institutional types and sociodemographic profiles. In doing so, the study aims to generate data that can inform institutional policies and educational strategies related to integrity in teacher education.

Specifically, the study is guided by the following research questions (RQ):
RQ1: How do academic managers perceive the prevalence, evolution, and severity of different forms of academic dishonesty among students enrolled in PTTPs?
RQ2: Which dishonest behaviours are perceived as the most serious, most prevalent, and most rapidly evolving, particularly in relation to the use of generative AI?
RQ3: To what extent do perceptions of academic dishonesty vary according to the key characteristics of academic managers; for example, age, gender, years of teaching experience, academic management experience, type of university (public or private), and level of study (undergraduate or postgraduate)?
RQ4: Can a composite index be developed to comprehensively rank dishonest behaviours based on their perceived prevalence, evolution, and severity, as assessed by academic management staff?

2. Methodology

2.1. Sample

The sample for this study comprises 198 academic managers serving in roles such as coordinators and directors of PTTPs at both undergraduate and postgraduate levels. Participants were selected from a wide range of institutional contexts, thereby ensuring representation across diverse educational settings. By capturing a broad spectrum of perspectives related to academic integrity within teacher education, this diversity contributes to the robustness of the findings. Table 1 presents a detailed summary of the key descriptive variables characterising the participant group.

Table 1: Descriptive variables of the sample

Variable		Percentage
Sex	Female	61.62 %
	Male	38.38 %
Age*	20 – 40 years old	31.12 %
	41 – 55 years old	56.63 %
	+ 55 years old	12.24 %
Years of teaching experience	1 – 10 years	23.74 %
	11 – 15 years old	30.81 %
	+ 15 years	45.45 %
Years of experience in positions of responsibility and management in initial teacher training studies	0 – 3 years	51.52 %
	4 – 7 years	32.32 %
	+ 8 years	16.16 %
Academic level of the degrees in which the participants exercise their responsibility or academic management	Degree	60.61 %
	Graduate	29.29 %
	Both	10.10 %
Type of university	Public	81.31 %
	Private	18.69 %

Note. The percentages in this variable are calculated on the valid answers (n = 196), since 2 participants did not answer this question.

The selection process for this sample consisted of identifying all Spanish universities (both public and private) that offer degrees linked to the PTTPs. To do this, the official list available on the website of the Ministry of Universities of the Government of Spain (https://www.universidades.gob.es/listado-de-universidades/) was consulted, with the aim of identifying the academic heads of these studies. To be recognised as an academic manager, the criterion was established that each participant must occupy a position as the director of a master's degree course, coordinator of academic programmes, head of studies, director of studies or vice-dean with responsibilities assigned to specific areas or degrees linked with PTTPs.

In October 2024, we invited 231 academic managers via email to participate in our research. Three reminders were sent during the data collection period, which ended in December 2024. Ultimately, 198 academic managers completed the questionnaire, resulting in a response rate of 85.7%. This rate significantly exceeds the average online survey response rate of 44.1%, as reported in a meta-analysis by Saleh and Bista (2017), thereby strengthening the validity and representativeness of our findings.

2.2. Data collection instrument and procedure

The online anonymous questionnaire comprised three sections and received approval from the Ethics Committee of the University of the Balearic Islands (ref. 31CER24). In accordance with ethical research standards, participation in the study was entirely voluntary and fully anonymous. Before accessing the questionnaire, participants were required to read an introductory document outlining the purpose, scope, and ethical safeguards of the study. This document clearly explained the nature of the research, data handling procedures, the anonymous nature of the responses, and the participants' right to withdraw at any time without consequence.

Only those individuals who explicitly gave their informed consent were granted access to the survey. Consent was obtained digitally via a clear affirmative action, ensuring that all participants had sufficient information to make an autonomous and informed decision to participate. This process aligns with the international ethical standards for human subject research, as well as the guidelines established by the UIB Ethics Committee.

The design of the questionnaire involved adapting instruments from prior studies on academic integrity (Cerda-Navarro et al., 2023; Henning et al., 2020). External validation was conducted between March and May 2024 by ten Spanish national experts in academic integrity and social research methodology, and a pilot test was conducted with 11 former academic managers/coordinators from three Spanish universities.

Experts were purposively selected to ensure complementary profiles and contextual relevance, subject to three criteria: (a) domain expertise in academic integrity and/or assessment (documented by a doctoral degree and/or ≥3 peer-reviewed outputs); (b) methods expertise in survey design/psychometrics; and (c) Spanish higher-education experience (preferably in teacher education programmes).

Experts judged each item on three dimensions: (1) relevance/representativeness to dishonesty in PTTPs; (2) clarity/linguistic adequacy for Spanish academic managers; and (3) domain coverage (redundancy/gaps). We used a 4-point scale (1 = not relevant/unclear; 4 = highly relevant/very clear) with free-text comments and suggestions for rewording.

In terms of quantifying content validity and decision rules, for each dimension we computed the Item-level Content Validity Index (I-CVI) (proportion of experts rating 3 or 4) and the scale-level CVI (S-CVI/Ave) (mean of I-CVIs across items). Following widely used thresholds for panels of 6–10 experts, items with I-CVI ≥ .78 were retained, .70–.77 were revised and re-rated, and < .70 were removed or replaced (Polit et al., 2007). We also report the percentage agreement for relevance and clarity.

With regard to procedure and outcomes, two iterative rounds were conducted. After Round 1, five items were reworded for clarity, two items were merged to remove redundancy, and three GenAI-related items were added, based on expert recommendations. Round 2 yielded I-CVI 0,87, I-CVI (clarity) 0,79, S-CVI/Ave (relevance) 0,86, S-CVI/Ave (clarity) 0,81, percent agreement (relevance) 87%, and percent agreement (clarity) 82%. To ensure comprehensibility and timing, we then conducted a pilot/cognitive debrief with 11 former academic managers from three Spanish universities, after which minor phrasing changes were made accordingly.

The 28 behaviours constitute a formative typology (a content domain), rather than a single reflective latent construct; therefore, internal consistency coefficients or factor analyses are not appropriate for the item set itself. Reliability pertains to the rating scales (prevalence, evolution, severity), for which anchors/examples were standardised and piloted during the cognitive debrief.

This rigorous process aligns with the recommendations made by Newton (2024) for ensuring the reliability of academic integrity surveys. We selected a cross-sectional quantitative survey to obtain population-level estimates of the perceived prevalence, evolution, and severity of 28 behaviours and to test between-group differences with adequate statistical precision. These requirements are less well served by qualitative designs but are essential for constructing the prioritisation index (DB-PES).

This article focuses on the first section of the questionnaire, in which participants were asked to evaluate the prevalence, evolution, and perceived severity of 28 dishonest academic behaviours. Responses were collected using 5-point Likert scales tailored to each dimension; this method is consistent with instruments used on other similar studies (Adesile et al., 2016).

2.3. Data analysis
Based on the results obtained, a representative metric index was calculated for each dishonest behaviour, integrating the results of the three variables analysed: prevalence, evolution, and severity. This process involved several statistical procedures. Firstly, the arithmetic means for each variable were calculated separately for each dishonest behaviour, considering only valid responses. After that, the individual means were combined through averaging to obtain a total mean. This allowed for a structured ranking of dishonest behaviours according to their perceived frequency, evolution, and severity among students enrolled in PTTPs.

In so doing, the following procedure was followed: first, the arithmetic mean of the valid answers to the questionnaire was calculated for each variable and each item. Subsequently, a global arithmetic mean was obtained, averaging the individual means of each variable, which allowed for a single final score—called the total mean—to be obtained (1 to 5). In this way, a ranking was obtained for the dishonest behaviours that are considered most common, present and severe among students of PTTPs.

Statistical analysis was conducted using the statistical software R (version 2024.12). Given the characteristics of the data, non-parametric statistical tests were employed due to the violation of normality assumptions verified by Shapiro-Wilk normality tests (Ghasemi & Zahediasl, 2012). Specifically, Mann-Whitney U tests were used for comparisons between two independent groups, while Kruskal-Wallis H tests, complemented by Dunn's post hoc comparisons with Bonferroni corrections, were utilised to analyse the differences among three or more independent groups (Dinno, 2015).

Moreover, descriptive statistics were calculated, including mean ranks and standard deviations, to enhance the interpretation of the findings. The resulting data facilitated the calculation of the DB-PES Index (Dishonest Behaviours according to their Prevalence, Evolution and Severity), categorising behaviours into high, medium, and low levels based on their total mean scores.

3. Results
3.1 Academic managers' perceptions of the prevalence, evolution, and severity of different forms of academic dishonesty among students enrolled in PTTPs
Based on the obtained data, a representative score was calculated for each dishonest practice, integrating the scores of the three variables analysed for each dishonest behaviour: prevalence, evolution and severity. Table 2 presents the dishonest behaviours analysed in the study, ordered from highest to lowest, based on their total mean score. This score integrates the average values of the three variables considered—prevalence, evolution, and severity—allowing for a comprehensive ranking that reflects how frequently each behaviour occurs, how it has evolved over time, and how serious it is perceived to be by academic staff.

Table 2: Dishonest behaviours ordered by their total mean, considering the three variables analysed

Dishonest Conduct	**Total Average**
C21. Use AI tools to generate answers in an assessable activity without making it explicit or known to teachers	4.32
C24. Present an essay/assignment/bachelor's or master's dissertation (BMD) generated partially or completely by AI as their own without making it explicit or making it known to the teaching staff	4.23
C22. Use AI applications for translation or automatic paraphrasing without citing sources	4.18
C25. Modify an essay/assignment/BMD that had been partially or completely prepared using AI to hide its automated origin	4.15
C23. Use AI in online exams (where not allowed by the teacher)	4.07
C9. Present an assessable activity with verbatim copying of texts without citing their origin or with indirect quotations (paraphrases) without citing the sources	3.90
C.28 Falsify research results using AI	3.82
C5. Copy in an online assessable activity with the help of technological devices (phones, earpieces, etc.), instant messaging applications (WhatsApp, Telegram, WeChat, etc.) or social networks (Facebook, Instagram, TikTok, etc.)	3.80
C27. Pay for AI services that specialise in performing academic tasks	3.80
C15. Pay a person or company for the completion of assessable activities/BMD	3.68
C7. Present an assessable activity carried out by another person as one's own	3.60
C20. Make excuses or seek false alibis to justify a delay in the delivery, attendance or fulfilment of an academic obligation	3.56
C16. Complete assessable activities/BMD for another student and charge for it	3.41
C13. Present as new and original an assessable activity already carried out and delivered by another student in the same subject or in other subjects	3.38
C26. Use AI to obtain potential assessment test statements	3.38
C14. Submit an assessable activity downloaded from an online repository of essays and assignments	3.35
C11. Include a classmate's name in an assessable activity in which he/she has not actually participated	3.31
C12. Present as new and original an assessable activity of one's own that has already been evaluated in another subject or in another course	3.29
C2. Copy from unauthorised notes, books, or materials in an assessable activity	3.26
C19. Fail to inform the teaching staff or academic authorities of known cases of fraud committed by other students in evaluation processes	3.21
C3. Copy from another student in a written exam or test	3.20
C18. Forge official documents (language level certificates, transcripts, diplomas, etc.) that allow an assessment test to be validated	3.10
C8. Extract/retrieve statements from an assessment test before it is taken	3.08
C4. Allow one's own work to be copied by another student in an assessable activity	2.98
C17. Obtain preferential treatment from administrative or teaching staff to obtain some personal benefit (e.g. to receive a research grant or scholarship, obtain better internship placements, etc.)	2.94
C10. Exclude the name of a classmate in an assessable activity in which he/she has participated	2.90
C6. Impersonate someone else on an assessment test or written exam	2.90
C1. Copy using ad hoc or prepared 'cheat sheets' in an assessable activity	2.82

3.2 Dishonest behaviours identified as the most serious, most prevalent, and most rapidly evolving, particularly in relation to the use of generative AI

Derived from Table 2, the DB-PES Index has been developed, which classifies the various dishonest practices according to the scores achieved in the three variables analysed, thereby providing a comprehensive view of their relevance and perception. In this way, dishonest behaviours have been organised into three categories, including high, medium and low index. A total of 28 behaviours have been analysed, with the first nine (C21, C24, C22, C25, C23, C9, C28, C5, C27) corresponding to the high DB-PES index, the next 10 (C15, C7, C20, C16, C13, C26, C14, C11, C12, C2) to the medium DB-PES index, and the last nine (C19, C3, C18, C8, C4, C17, C10, C6, C1) to the low DB-PES index.

The five highest-ranked forms of misconduct, all directly related to the use of AI, highlight a significant shift in the modalities of academic dishonesty, as perceived by the academic staff responsible for managing PTT degrees. This pattern points to two key issues. First, the rapid integration of AI into students' academic practices has surpassed the pace of institutional regulation, pedagogical adaptation, and ethical guidance. Second, from the perspective of those overseeing academic programmes, the undisclosed use of AI is not only highly prevalent but also perceived as one of the most severe threats to the integrity of evaluation processes.

Although AI-related misconduct dominates the top of the ranking, traditional dishonest practices remain visible in the data. Practices such as verbatim copying without citation (3.90), cheating with technological devices during online assessments (3.80), and paying for the completion of academic work (3.68) continue to be perceived by academic staff as widespread, severe and actual. This co-existence of conventional and new forms of cheating suggests that generative technologies have not replaced traditional misconduct but rather expanded the range and complexity of dishonest behaviours.

Notably, actions such as submitting a peer's work as one's own (3.60) and providing false excuses to avoid academic obligations (3.56) are still viewed as being relatively common, though slightly less severe than AI-related behaviours. This could indicate a recalibration of perceived ethical boundaries; whereby technological deception is viewed as being more serious or more systematically damaging than person-to-person misconduct.

Towards the lower end of the ranking, behaviours such as impersonation during an exam (2.90), the use of cheat sheets (2.82), and excluding a peer's name from a group task (2.90) receive lower average scores. From the viewpoint of the academic respondents, these may be less frequent due to logistical or contextual factors, such as increased supervision or changes in assessment formats. Alternatively, the severity or prevalence of these behaviours may not appear to have evolved substantially in recent years.

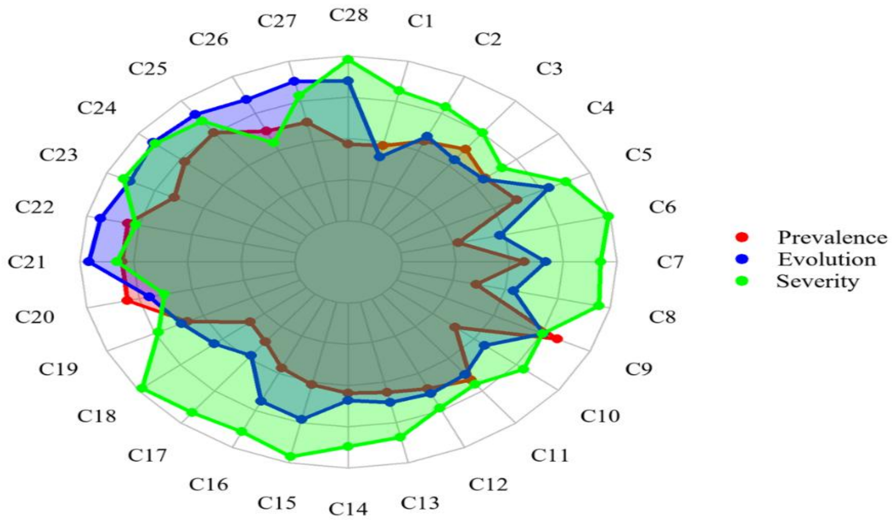

Figure 1: Distribution of the scores obtained in each conduct per variable analysed

The analysis reveals that the scores associated with the severity variable are consistently higher than those for prevalence and evolution (see Figure 1). This suggests that, regardless of how widespread or increasingly prevalent a dishonest behaviour may be, academic managers generally perceive most of these practices to represent serious threats to academic integrity. The behaviours considered most severe are those involving substantial ethical violations or a direct compromise of academic standards, such as impersonation during an exam (C6), forgery of official documents (C18), falsification of research using AI (C28), paying for academic work (C15), accessing exam content beforehand (C8), presenting others' work as one's own (C7), seeking undue academic privileges (C17), and using AI during online exams without permission (C23).

With regard to the evolution variable, a more diverse pattern emerges, marked by significant increases in certain behaviours over the past decade. Notably, dishonest practices involving artificial intelligence—such as using AI to generate answers (C21), automatic translation or paraphrasing without citation (C22), unauthorised AI use in exams (C23), or concealing the origin of AI-generated work (C25)—are viewed as having undergone the most marked increase. This perception reflects a growing concern among academic staff regarding the rapid integration of AI tools into student behaviours and the limited institutional preparedness to address these new forms of misconduct.

In contrast, the prevalence scores tend to be lower than those of the other two variables. Behaviours considered most serious from an ethical standpoint—such as seeking favours from academic staff (C17), stealing or accessing test content prior to its administration (C8), forging documents (C18), and impersonation (C6)—are also perceived as less common. Meanwhile, the two behaviours considered most prevalent—copying or paraphrasing without proper citation (C9) and making false excuses to avoid academic obligations (C20)—suggest recurring issues with students' information literacy skills and a broader pattern of low academic responsibility. Although they are perceived as being less severe individually, these behaviours nevertheless reflect attitudes that undermine academic norms and reveal a lack of commitment to ethical standards.

3.3 Variations in academic managers' perceptions of academic dishonesty across age, gender, teaching experience, academic management experience, university type, and study level

This section presents the analysis of statistically significant differences between the perceived prevalence, evolution, and severity of dishonest academic behaviours and the descriptive variables of the sample (Table 1). Given that the assumptions of normality were not met, non-parametric statistical tests were employed. As summarised below, the results highlight the relationships between participants' sociodemographic and professional characteristics and their perceptions of academic dishonesty.

Table 3: Differences between perceptions of academic dishonesty and descriptive variables of the sample

Variable	Descriptive variable	Test	Statistical	P value
Prevalence	Type of University	Mann-Whitney U	U = 1814	< .001***
Prevalence	Age	Kruskal-Wallis Dunn 41-55 - + 55	$\chi 2(2) = 9.60$ $z = 2.92$	< .01** < .05*
Prevalence	Level	Kruskal-Wallis Dunn Both – Postgraduate	$\chi 2(2) = 7.83$ $z = 2.79$	< .05* < .05*
Prevalence	Years of Teaching Experience	Kruskal-Wallis Dunn 11-15 - + 15	$\chi 2(2) = 16.00$ $z = 3.98$	< .001*** < .001***
Prevalence	Years of Experience Positions	Kruskal-Wallis Dunn 0-3 - 4-7	$\chi 2(2) = 8.56$ $z = -2.78$	< .05* < .05*
Evolution	Type of University	Mann-Whitney U	U = 1836	< .001***
Evolution	Age	Kruskal-Wallis Dunn 20-40 - + 55	$\chi 2(2) = 7.85$ $z = 2.80$	< .05* < .05*
Evolution	Years of Teaching Experience	Kruskal-Wallis Dunn 1-10 - 11-15 11-15 - + 15	$\chi 2(2) = 33.03$ $z = -3.10$ $z = 5.69$	< .001*** < .01** < .001***

Gravity	Level	Kruskal-Wallis Dunn Both – Degree Both - Postgraduate	$\chi2(2)$ = 15.23 z = 3.86 z = 3.43	< .001*** < .001*** < .01**
Gravity	Age	Kruskal-Wallis Dunn 20-40 - 41-55	$\chi2(2)$ = 8.13 z = - 2.74	< .05* < .05*
Gravity	Years of Experience Positions	Kruskal-Wallis Dunn 0-3 - 4-7 4-7 - +8	$\chi2(2)$ = 28.98 z = 4.90 z = - 4.21	< .001*** < .001*** < .001***

Note. Non-parametric tests (Mann-Whitney U and Kruskal-Wallis with Dunn's post hoc test) were used due to lack of normality in the data. Significance levels: p < .05 = significant (***), p < .01 = very significant (**), p < .001 = extremely significant (*).

Regarding the prevalence of dishonest behaviours, significant differences were found according to the type of university. Participants affiliated with public universities ($\bar{X}$ = 2.96) reported significantly higher perceptions of the prevalence of dishonest practices compared to those from private institutions ($\bar{X}$ = 2.64) (U = 1814, p < .001). While this difference is statistically significant, caution is warranted due to the sample imbalance, with 81.3% of respondents representing public universities.

Age also emerged as a significant factor ($\chi^2(2)$ = 9.60, p < .01), with participants aged 41–55 ($\bar{X}$ = 2.91) perceiving a higher prevalence of dishonest practices compared to those over 55 years old ($\bar{X}$ = 2.72) (z = 2.92, p < .05). Similarly, the level of studies at which participants teach showed significant differences ($\chi^2(2)$ = 7.83, p < .05). Respondents who work across both undergraduate and postgraduate levels ($\bar{X}$ = 3.12) perceived dishonest behaviours as being more prevalent compared to those working exclusively at the postgraduate level ($\bar{X}$ = 2.86) (z = 2.79, p < .05).

Years of teaching experience also influenced perceptions of prevalence ($\chi^2(2)$ = 16.00, p < .001). Specifically, educators with 11–15 years of experience ($\bar{X}$ = 3.07) perceived dishonest behaviour as being more prevalent compared to those with more than 15 years of experience ($\bar{X}$ = 2.64) (z = 3.98, p < .001). Similarly, significant differences were found based on years in academic or managerial positions ($\chi^2(2)$ = 8.56, p < .05), with those having 4–7 years of such experience ($\bar{X}$ = 3.02) perceiving a higher prevalence of dishonest behaviour than their counterparts with 0–3 years ($\bar{X}$ = 2.82) (z = -2.78, p < .05).

With respect to the perceived evolution of dishonest behaviours over time, significant differences were again observed according to the type of institution. Respondents from public universities ($\bar{X}$ = 3.46) reported perceiving a greater increase in dishonest practices than those from private institutions ($\bar{X}$ = 3.20) (U =

1836, $p < .001$), though, as previously noted, this finding may be partially influenced by sample composition.

Age-based differences were also identified (χ^2 (2) = 7.85, $p < .05$), with respondents aged 20–40 ($\bar{X}$ = 3.50) reporting a significantly greater perception of increased dishonest behaviours than those aged over 55 ($\bar{X}$ = 3.31) (z = 2.80, $p < .05$). Teaching experience also showed a notable influence (χ^2 (2) = 33.03, $p < .001$). Participants with 11–15 years of experience ($\bar{X}$ = 3.55) perceived a greater increase in dishonest practices than both those with 1–10 years ($\bar{X}$ = 3.43) (z = -3.10, $p < .01$) and those with more than 15 years of experience ($\bar{X}$ = 3.21) (z = 5.69, $p < .001$).

In terms of severity, significant differences were observed based on the level at which respondents teach (χ^2 (2) = 15.23, $p < .001$). Educators teaching at both undergraduate and postgraduate levels ($\bar{X}$ = 4.51) perceived dishonest behaviours as being significantly more severe than those exclusively teaching undergraduate ($\bar{X}$ = 4.03; z = 3.86, $p < .001$) or postgraduate courses ($\bar{X}$ = 4.08; z = 3.43, $p < .01$).

Age-related differences also emerged ($\chi^2(2)$ = 8.13, $p < .05$). Respondents aged 41–55 ($\bar{X}$ = 4.14) rated dishonest practices as more severe compared to those aged 20–40 ($\bar{X}$ = 4.00) (z = -2.74, $p < .05$). Finally, significant differences were found concerning years of experience in academic management or leadership positions (χ^2 (2) = 28.98, $p < .001$). Interestingly, those with 4–7 years in such roles ($\bar{X}$ = 3.77) reported significantly lower perceptions of severity compared to those with 0–3 years ($\bar{X}$ = 4.24; z = 4.90, $p < .001$) and those with more than eight years of experience ($\bar{X}$ = 4.28; z = -4.21, $p < .001$).

4. Discussion

The findings of this study confirm a pressing concern among academic managers responsible for PTTPs, who report that the integrity of academic practices is being challenged both by persistent traditional misconduct and by the emergence of generative artificial intelligence (GenAI). This trend has also been evidenced and systematically documented in recent literature reviews, such as that conducted by Bittle and El-Gayar (2025). From their perspective, the problem is neither static nor isolated but evolving rapidly.

Our results indicate that academic coordinators perceive traditional forms of misconduct (e.g. plagiarism, collusion, and cheating in online exams) as prevalent and persistent, while also placing several GenAI-related behaviours among the most frequent and most serious. This mixed pattern (with "*old*" and "*new*" forms co-existing) mirrors international evidence. Large multi-institutional studies have shown that contract cheating, and plagiarism remain entrenched (e.g. Bretag et al., 2019; Comas-Forgas et al., 2025), while recent empirical work documents the rapid uptake and normalisation of GenAI-assisted writing and paraphrasing in assessment contexts (Abbas et al., 2024; Cotton et al., 2024; Gustilo et al., 2024). Such findings support the validity of our prevalence and severity rankings.

The salience of GenAI-related behaviours in our index is consistent with emerging evidence that undisclosed GenAI use is both common and difficult to regulate. In a business-school context, Gonsalves (2024) reports high non-compliance with mandatory GenAI-use declarations, driven by ambiguity about "acceptable" levels of assistance and fear of sanction. In line with this, a real-world "Turing test" of a UK examinations system found that 94% of fully GenAI-written submissions passed undetected and received, on average, higher grades than human work, emphasising the detection challenge and the need to redesign assessment and policy (Scarfe et al., 2024). Together with survey-based evidence linking GenAI use to instrumental motives and mixed learning outcomes (Abbas et al., 2024), these studies align with our respondents' judgments that GenAI-enabled behaviours are both prevalent and severe.

At the same time, coordinators' views that "traditional" misconduct remains common accord with prior work. In Australia, a national survey documented non-trivial self-reports of contract cheating as well as a broad ecosystem of outsourcing options (Bretag et al., 2019), and a systematic review of online exam cheating shows sizeable self-admission rates and clear opportunities for misconduct, particularly in unproctored or poorly designed assessments (Newton & Essex, 2023; Noorbehbahani et al., 2022). Our findings therefore echo a dual reality, which is that even as GenAI introduces new forms of boundary-blurring and authorship ambiguity, long-standing behaviours remain part of the integrity crisis that teacher education programmes must address.

Regarding severity, the consistently high ratings for identity fraud (impersonation) and document falsification in our data are consistent with the broader literature that recognises these behaviours as among the most egregious forms of misconduct, given their direct threat to credential validity and public trust (see e.g. summaries in Cerdà-Navarro et al., 2025: Newton & Essex, 2023; Noorbehbahani et al., 2022). Evidence that GenAI-generated work can evade detection in high-stakes contexts (Eaton-Merkle, 2024; Scarfe et al., 2024) further justifies coordinators' concerns regarding behaviours that compromise authorship verification.

Furthermore, our respondents perceived an increase in misconduct over the last five to ten years, particularly in online assessments. This perception aligns with reviews showing that the emergency pivot to remote exams during the COVID-19 pandemic amplified opportunities for (and admissions of) cheating (Comas-Forgas et al., 2021). Notably, many institutions continue to rely on unsupervised online formats with limited proctoring (Malhotra et al., 2025). Although estimates vary by method and context, the direction of change noted by coordinators is well supported.

With regard to the factors associated with misconduct and its detection, our findings concerning the limitations of purely "authentic" assessment strategies are consistent with studies showing that authenticity alone does not "immunise" tasks against outsourcing or GenAI assistance; in practice, even highly authentic tasks have been outsourced or GenAI-augmented (Ellis et al., 2020; Harper et al., 2021; Kofinas et al., 2025). The implication is not to abandon authentic design, but to combine it with oral defences, iterative supervision, and transparent GenAI-use policies that clarify which forms of assistance are permitted and how they must be declared (Cotton et al., 2024; Gustilo et al., 2024; Moya Figueroa & Eaton, 2023).

Finally, our exploratory patterns on demographic and professional correlates should be read alongside mixed prior evidence. In a 22-language cross-national study, Awdry and Ives (2023) found that individual demographics (e.g. age, gender) were generally weak predictors of contract cheating once peer-norms and contextual factors were accounted for, whereas discipline and perceived peer behaviour were more salient. This aligns with our own observation that contextual and normative dimensions in programmes may matter at least as much as personal characteristics.

Finally, a plausible explanation for the observed "severity–prevalence" paradox—whereby those behaviours that are judged most egregious (e.g. impersonation, document falsification) are relatively infrequent—lies in the joint effects of opportunity structures and deterrence. Severe behaviours typically require higher coordination, leave stronger audit trails, and occur in tightly controlled settings (e.g. identity checks, invigilated/high-stakes exams), which elevates the likelihood of detection. Deterrence research consistently finds that the certainty and frequency of enforcement, rather than the harshness of sanctions, are most likely to reduce violation rates (Buckenmaier et al., 2021; Eriksson & McGee, 2015; Finelli et al., 2003; Teodorescu, 2021).

Empirically, measures that increase monitoring certainty—such as live/online proctoring—are associated with performance patterns consistent with reduced cheating, supporting lower base rates for severe infractions (Alessio et al., 2018; Oeding, 2024). By contrast, lower-severity behaviours (e.g. text-based plagiarism, low-friction collusion) are cheaper, easier, and often embedded in assessment ecologies with variable detection/enforcement, which helps explain their higher prevalence despite lower perceived seriousness (Bretag et al., 2019; McCabe & Treviño, 1993; Noorbehbahani et al., 2022). Together, these mechanisms explain why the most severe behaviours are uncommon while more "mundane" forms remain widespread.

To deepen the theoretical grounding of our results, we interpret the DB-PES rankings through established ethical frameworks. First, Rest's Four-Component Model helps explain the prominence of GenAI-related behaviours by asserting that ambiguous institutional policies can blunt moral sensitivity (is AI "assistance" wrong here?), contested norms complicate moral judgment, strong instrumental incentives erode moral motivation, and low-effort digital affordances test moral character in day-to-day work (Rest, 1986; Thoma & Bebeau, 2013). Second, Jones's issue-contingent model clarifies the "severity–prevalence" paradox: behaviours with lower perceived moral intensity (e.g. text-based plagiarism via paraphrasers) score lower in terms of magnitude of consequences and concentration of effect, so they occur more often, whereas impersonation and document falsification are widely condemned, thereby reducing frequency despite high severity (Jones, 1991). Third, moral disengagement mechanisms—

such as the diffusion of agency to "the tool" and euphemistic labelling (e.g. "editing," "polishing")—help to account for rationalisations around GenAI use (Bandura, 1999). Finally, the lens of digital integrity within digital ethics reframes integrity as a sociotechnical practice requiring transparency about algorithmic assistance and accountability for authorship provenance; in this view, DB-PES is a priority-setting device to align policy, assessment design, and digital norms (Floridi, 2013).

Taken together, then, our findings resonate with, and add nuance to, an evolving body of evidence. Integrity risks in teacher education today reflect both enduring forms of misconduct and rapidly evolving GenAI misuse. Detection remains imperfect; authenticity assessment and policy innovations go some way towards tackling the problem but are not sufficient on their own. Furthermore, programme-level norms likely shape both behaviour and perceptions. Collectively, these insights ground our practical recommendations for clearer AI policies (including declaration requirements), assessment redesign that integrates verification opportunities (e.g. vivas, in-class components), and sustained integrity education for coordinators and students alike (Comas-Forgas et al., 2023; Gallent-Torres et al., 2023; Trajkovski & Hayes, 2025).

5. Conclusions

This study addressed the ways in which academic coordinators in Spanish teacher education programmes perceive the prevalence, evolution, and severity of 28 dishonest behaviours, including those involving generative AI; it also introduced the DB-PES index to prioritise institutional responses.

Findings show that GenAI-related behaviours are perceived as both highly severe and rapidly increasing, while traditional misconduct (e.g. plagiarism, contract cheating) remains common. Perceptions differ by age, institutional type, and management experience, and a "severity–prevalence" paradox emerges whereby the most egregious behaviours (e.g. impersonation, falsification) appear to be less frequent than lower-effort infractions. Together, these results portray academic dishonesty as a dynamic, multimodal phenomenon that strains legacy integrity policies as well as assessment practices. The DB-PES provides a transparent, replicable mechanism to triage risks and align limited resources with those behaviours deemed to most urgently require tackling.

Institutions should adopt explicit AI-use policies with disclosure requirements, redesign assessments to include authorship verification (e.g. oral defences, process evidence, staged drafts), and deliver sequenced integrity education for staff and students. The DB-PES can guide policy triage as well as the monitoring and evaluation of interventions. At the system level, we encourage international collaboration to develop interoperable AI-integrity standards and shared indicators. Future work should complement these results through qualitative inquiry to explain the contextual mechanisms behind the rankings and to evaluate the impact of policy and assessment reforms over time.

6. Limitations

This study provides useful knowledge about academic dishonesty in PTTPs, especially in relation to the recent challenges introduced by GenAI. However, several limitations must be taken into account when interpreting its results and conclusions. First, the study is based solely on the views of academic managers, such as programme coordinators and directors. It does not include input from students or teaching staff, which limits the possibility of comparing different viewpoints. Without student responses or direct observation, it is difficult to confirm how common certain behaviours are, or to understand what factors contribute to them.

Second, although the sample is relatively large (n = 198) and the response rate is high (85.7%), the majority of respondents work at public universities (81.3%). This may affect the applicability of the results to private institutions, which often differ in structure, resources, and regulations. Differences among Spanish universities, in terms of regional policies and teaching approaches, may also have influenced the results. Third, the study is cross-sectional. It gathers data from one point in time and therefore cannot show changes in behaviour or attitudes over the years. Given the rapid adoption of GenAI in academic settings, future studies would benefit from a long-term design that tracks patterns and responses over time.

Fourth, the DB-PES index, developed by the authors, combines managers' ratings of prevalence, change, and seriousness of dishonest behaviour. While it is a useful classification tool, it reflects personal assessments, rather than confirmed cases. Such perceptions may be shaped by individual experiences, public discussion, or differing levels of contact with student misconduct. Lastly, although the questionnaire was tested and reviewed by experts, its structure may limit the amount of detail respondents could provide, especially with regard to sensitive or complex ethical issues. Including interviews or open comments could have added more information on the ways in which managers identify and deal with academic dishonesty.

Despite these limitations, the study follows a sound methodology, uses validated instruments, and meets ethical research standards. By examining academic dishonesty as perceived by academic managers, it addresses a topic that has received little attention to date and presents data that can support practical changes in policy, staff preparation, and programme development in the context of adopting novel technologies in education.

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Disclosure statement
The authors report that there are no competing interests to declare.

Data availability
The data that support the findings of this study are available on request from the corresponding author.

AI use declaration
The authors used ChatGPT-4.0 solely for proofreading, limited to grammar, clarity, and style. All conceptual content remains the authors' own. AI assistance did not influence analysis, interpretation, or authorship and was fully reviewed and approved by the authors.

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