PlagiAct: Measurement Instrument of STEM Student Attitudes Toward Academic Dishonesty in the AI Era

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***Abstract*—*Contribution:* This study presents PlagiAct-V3, an empirically explored and stabilized instrument to assess science, technology, engineering, and mathematics (STEM) students' attitudes toward plagiarism in the era of generative AI.**
***Background:* The rapid rise of tools like ChatGPT has reshaped academic dishonesty. Existing instruments on plagiarism and generative AI (GenAI) lack a robust underlying theoretical basis, clear multidimensional structures, and comprehensive psychometric validation, especially in STEM and European contexts. PlagiAct addresses this gap by integrating four complementary theories, adding GenAI-specific items, and exploring a multidimensional structure with 725 STEM students.**
***Research Questions:* Which factors influence STEM students' attitudes toward plagiarism in digital contexts? What is the factorial structure of plagiarism attitudes?**
***Methodology:* PlagiAct-V2 was developed through a literature review, expert content validation, and pretesting, and was administered to 725 engineering students from five Spanish universities. Internal consistency was examined using Cronbach's alpha and McDonald's omega, while exploratory factor analysis was used to examine the structure of the attitude scales, yielding eight empirically derived dimensions. These analyses led to the final PlagiAct-V3 instrument. Main limitations include convenience sampling, potential selection bias, and the need for periodic revalidation as GenAI practices evolve.**
***Findings:* Results provide evidence of satisfactory internal consistency and exploratory structural validity. The findings highlight the multidimensional nature of plagiarism attitudes in the digital age and offer an empirically grounded basis for designing targeted interventions to promote academic integrity.**

***Index Terms*—AI-giarism, generative AI (GenAI), higher education (HE), measurement instrument, plagiarism, science, technology, engineering, and mathematics (STEM).**

I. Introduction

PROFESSIONAL and academic ethics are highly relevant in the educational sphere, particularly in higher education (HE) [1]. One of the most significant ethical challenges faced by HE institutions is plagiarism, defined as presenting another's work as one's own without proper attribution [2].

This concern has been amplified with the steady increase in the use among students of generative AI (GenAI) tools [3], [4], particularly when they use their outputs without attribution (a.k.a. AI-giarism). Although such use may not always align with traditional definitions of plagiarism, it reflects the same core issue: misrepresenting authorship. In this study, we adopt a broad interpretation of plagiarism, encompassing any dishonest representation of work—regardless of whether it originates from a human or a machine [5], [6].

Although GenAI technologies offer clear advantages, over-reliance on them—much like traditional forms of plagiarism—has profound consequences for academic institutions. AI-giarism not only undermines institutional credibility but also raises doubts about degree integrity [7], [8]. Moreover, AI-giarism hampers students' intellectual growth by disrupting knowledge consolidation—the transfer of information into long-term memory through reflection and practice. By bypassing these steps, students weaken retention and hinder deep learning, often replacing critical thinking with technological shortcuts. In science, technology, engineering, and mathematics (STEM) disciplines, these risks are even more pronounced, as they threaten foundational values such as credibility, originality, and innovation [1], [9], as well as core competencies like critical thinking and problem-solving [10]. Additionally, the accuracy and objectivity of AI-generated content remain problematic; uncritical use of these tools can expose students to misinformation and bias [10].

To address these challenges, institutions are increasingly redesigning assessments to promote creativity and analytical thinking, while also implementing clear policies for the ethical

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use of GenAI [11]. However, effective policymaking requires robust instruments capable of capturing both students' attitudes toward GenAI misuse and the factors shaping them [8], [12], [13]. Given the rapid evolution of GenAI tools and student perceptions, these instruments should support continuous evaluation to enable evidence-based updates of institutional policies and teaching practices [14].

Although several questionnaires exist to measure attitudes toward traditional plagiarism [15], [16], [17], they do not fully capture the changes introduced by GenAI. Therefore, in recent years, a small number of instruments have been proposed to address AI-giarism and related attitudes toward GenAI use in academic work, including the ATAQ [18], the AI Academic Integrity Scale [19], and exploratory questionnaires on broader student perceptions of GenAI [20], [21], [22], [23]. However, important limitations remain. Many instruments lack a strong theoretical grounding [18], [21], [22] or rely on a single framework such as the Theory of Planned Behavior [15] or the Technology Acceptance Model [20]. Factor structures are often limited or unclear [18], [19], [20], psychometric evidence is frequently incomplete [21], [22], [23], STEM contexts remain underrepresented [20], [21], [23], and European validations are scarce [18], [19], [20]. Moreover, most instruments focus narrowly on attitudes without considering the individual, academic, technological, external, and institutional factors shaping them [18], [19], [20], [21], [22], [23]. To address these limitations, PlagiAct was developed as an instrument grounded in four complementary theories, enriched with GenAI-specific items, and evaluated with 725 Spanish STEM students, providing an empirically explored multidimensional structure of attitudes and influencing factors related to AI-giarism.

The remainder of this article is organized as follows. Section II outlines the theoretical framework and conceptual model underlying the development of the PlagiAct questionnaire. Section III describes the design process of the PlagiAct instrument. Section IV presents the reliability and exploratory structural validity analyses conducted to evaluate the psychometric properties of the PlagiAct-V3 instrument. Section V discusses its alignment with theoretical models, key contributions, implications, limitations, and future directions. Finally, Section VI summarizes the main findings and their relevance for addressing plagiarism in the GenAI era.

II. Theoretical Foundations and Conceptual Model

Plagiarism and AI-giarism are multidimensional phenomena shaped by academic pressure, emotional coping, cognitive biases, and social and normative influences [8]. These dimensions are explained by different complementary theories: Merton's strain theory and Lazarus and Folkman's stress and coping theory interpret plagiarism as a response to academic pressure and stress [24], [25]; Kahneman and Tversky's prospect theory explains how cognitive biases distort risk perception and normalize dishonest behavior [26]; and Ajzen's theory of planned behavior highlights the role of attitudes, subjective norms, and perceived control in shaping intentions to plagiarize [27].

Although prior research has proposed several conceptual models of plagiarism, many lack an explicit connection to these theoretical foundations, limiting their explanatory power and interpretation of results. To address this issue, in this work the most relevant conceptual models were reviewed, and the framework proposed by Husain et al. [28] was identified as one of the most comprehensive and suitable for the AI-giarism context. Its constructs were then examined in relation to the four behavioral theories, confirming that the model adequately captures motivational, cognitive, social, and contextual factors potentially associated with plagiarism-related behaviors. For this reason, it was adopted as the conceptual foundation for the development of the PlagiAct questionnaire.

This model identifies five categories of factors that may influence individuals' attitudes toward AI-giarism, as illustrated in Fig. 1:

1) *Institutional Factors (U):* Perceptions of unclear academic regulations (URs) and weak punishment for dishonest behavior (*UP*) may foster more permissive attitudes toward plagiarism [29], [30].
2) *Academic Factors (A):* Perceptions of task difficulty and relevance (*AT*) [31], [32], adequacy of teaching methods (AM) [31], and adequacy of assessment strategies (*AE*) may influence students' attitudes toward plagiarism.
3) *External Factors (E):* Subjective norms (*ES*), such as observing peers engage in dishonest behavior [33], [34], and cultural context (*EC*) [12], including perceived corruption levels [13], may normalize plagiarism and increase its social acceptance.
4) *Personal/Individual Factors (I):* Individual factors such as demographics (*ID*) [35], academic expectations (*IE*) [36], personality traits (*IP*) [35], [37], [38], prior dishonest behavior (*IX*) [39], [40], [41], cognitive ability (*IC*) [42], [43], academic motivation (Im) [44], self-efficacy (*IS*) [45], [46], perceived workload (*IW*) [42], and knowledge of what constitutes academic misconduct (*IK*) [29], [45], [47] may influence students' susceptibility to dishonest behavior and their attitudes toward plagiarism. Greater knowledge of academic misconduct and higher self-efficacy are generally associated with lower permissiveness toward plagiarism, whereas perceived workload and academic pressure may increase the temptation to engage in dishonest practices [48], [49], [50]. Personality traits may also play a role: neuroticism may increase susceptibility under stress, conscientiousness and agreeableness are typically associated with stronger academic integrity, extraversion may reduce dishonest behavior through peer support, and openness to experience may favor more flexible ethical interpretations. Additional socio-demographic and academic variables, such as academic performance, attendance, employment status, economic status, and experience with GenAI tools, may further shape attitudes toward AI-giarism.
5) *Technological Factors (T):* Easy access to online content and GenAI tools (*TA*) [29], [45], along with the perceived difficulty of detection (*TD*) [51], may also increase the likelihood of academic dishonesty.

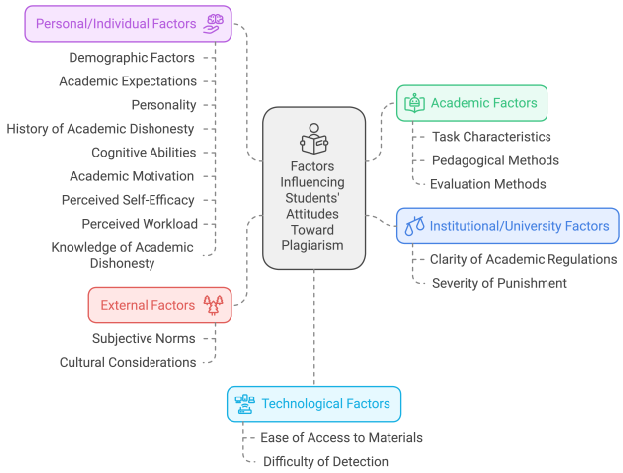

Fig. 1. Conceptual model (adapted from [28]). Generated with Napkin.ai.

III. Construction of the PlagiAct-V3 Measurement Instrument

The conceptual model shown in Fig. 1 guided the construction of the instrument. Following Hernandez-Sampieri and Mendoza [52], a five-step process was applied: design, content validation, pretesting, reliability analysis, and construct validation.

A. Step 1: Designing the Initial Questionnaire

The first step consisted of reviewing the literature to identify validated scales measuring plagiarism-related factors and attitudes. Three instruments were particularly relevant: Mavrinac et al. [15], Howard et al. [16], and Farooq and Sultana [17]. Since Howard and Farooq extend Mavrinac's original instrument, items from these scales were incorporated into the initial item pool. To incorporate a GenAI-specific perspective, nonredundant items from the technology acceptance model edited to assess ChatGPT adoption (TAME-ChatGPT) scale [53] were also included.

To avoid redundancy, overlapping items were removed. The remaining items were translated into Spanish and adapted to the engineering and GenAI context following the 2020 international test commission (ITC) guidelines [54]. Two of the authors classified the items according to the dimensions of the conceptual model (Section II), and new items were created to address uncovered constructs. These author-developed items are identified in [55, Appendix A]. All items used a 5-point Likert scale (1 = strongly disagree to 5 = strongly agree).

To assess personality, the BF-44 version of the Big Five instrument [56] was translated into Spanish following the same ITC guidelines. The questionnaire also collected socio-demographic data (e.g., gender, age, academic level, employment status, and aspirations) to analyze their influence on students' perceptions. This initial version was termed PlagiAct-V1.

B. Step 2: Content Validity

Content validity refers to the extent to which an instrument adequately represents its intended constructs. To assess the content validity of PlagiAct-V1, a panel of 10 experts in STEM education and research methodology (i.e., the authors not involved in the item classification process) reviewed the questionnaire using a structured guide covering the conceptual model, dimensions, and items. They evaluated item relevance, coherence, clarity, internal consistency, and completion time [52]. The experts confirmed the alignment between items and constructs and suggested minor wording revisions to improve clarity. Their feedback led to the development of PlagiAct-V2-Alpha, which was deployed online using Qualtrics.

C. Step 3: Pre-Test

The PlagiAct-V2-Alpha questionnaire was pretested with five Master's students from one of the participating universities to assess item clarity and completion time. Although no major clarity issues were identified, participants considered the questionnaire lengthy and repetitive. Nevertheless, all items were retained to preserve construct coverage. The final structure and item sources of PlagiAct-V2 are detailed in [55, Appendix A].[1]

D. Step 4: Reliability Analysis

PlagiAct-V2 operationalizes the dimensions defined in the conceptual model (Fig. 1) through a set of scales and subscales.

- A *Academic Factors (six items):* Includes items related to evaluation methods, teaching practices, and task characteristics.
- T *Technological Factors*: Includes two subscales: 1) ease of access to content (TA, three items) and 2) perceived difficulty of detection (TD, four items).
- U *Institutional Factors*: Includes regulation clarity (UR, two items) and perceived punishment severity (UP, one item).
- E *External Factors*: Includes subjective norms (ES, seven items).
- I *Individual Factors*: Includes knowledge (IK, five items), perceived workload (IW, one item), perceived self-efficacy (IS, two items), personality traits (IP, 44 items, with five subscales: Agreeableness (IP-A, nine items), Conscientiousness (IP-C, nine items), Neuroticism (IP-N, eight items), Openness to Experience (IP-O, ten items), and Extraversion (IP-E, eight items)), and additional socio-demographic variables (IO, 16 items: gender, year of birth, university, degree program, academic year, university admission system, admission score, academic aspiration, perceived academic performance, perceived study difficulty, class attendance frequency, employment status, scholarship status, economic status, primary academic goal, and level of experience with GenAI tools).

To assess attitudes toward AI-giarism, the two scales originally proposed by Farooq and Sultana [17] were adapted.

- DP *Positive Attitudes (26 items):* Measures agreement with statements that justify or normalize AI-giarism.

[1]The questionnaire can be found at https://ua.eu.qualtrics.com/jfe/form/SV_bOVEXijOGNzlHbo

TABLE I

RELIABILITY ANALYSIS RESULTS FOR THE SCALES INCLUDED IN THE PLAGIACT-V2 INSTRUMENT. #I: INITIAL NUMBER OF ITEMS, α: CRONBACH' ALPHA. ω: MCDONALD' OMEGA

Scale	#I	α	ω	Decision
A	6	0.836	0.833	Keep
TA	3	0.796	0.800	Keep
TD	4	<0.7	<0.7	Keep TD4
UR	2	0.778	-	Keep
UP	1	-	-	Keep
ES	7	<0.7	<0.7	Keep ES5
IK	5	<0.7	<0.7	Keep IK1 and IK2
IW	1	-	-	Keep
IS	2	<0.7	-	Keep IS1 and IS2
IP-E	8	0.778	0.776	Keep
IP-A	9	0.742	0.742	Remove items 2, 12, 27, 37
IP-C	9	0.764	0.766	Remove items 8, 18, 23, 43
IP-N	8	0.781	0.775	Keep
IP-O	10	0.814	0.815	Remove items 35, 41, 44
DP	26	0.919	0.916	Retain for EFA
DN	20	0.906	0.904	Retain for EFA

DN *Negative Attitudes (20 items):* Measures disapproval of AI-giarism. Items were reverse-coded so that higher scores consistently reflected more permissive attitudes.

IV. RESULTS

Based on a Spanish population of approximately 2 70 000 engineering students, the minimum required sample size was calculated to be 384. The details of this estimate calculation are provided in [55, Appendix B].

Given the questionnaire's length, a convenience sample, which is widely used in educational and social science research [57], was drawn from students accessible through the authors' institutions. Ethical approval was obtained from the five Spanish on-site universities participating in the study, and all analyses were performed in SPSS v29 and R.

The PlagiAct-V2 questionnaire was distributed online via Qualtrics between November 2023 and May 2024. Participants received an information sheet outlining the study's purpose and conditions for informed consent.[2] A total of 1336 responses were collected from engineering students across the five universities and twelve engineering degree programs. After applying the inclusion criteria, 725 valid responses (54.3%) were retained. Inclusion criteria included consent, completion of at least 66% of the questionnaire (including both attitude scales), and a minimum response time of five minutes. Details of the sample by university, degree, and gender can be seen in [55, Appendix C].

In classical test theory (CTT), internal consistency is commonly estimated with Cronbach's alpha (α) [58]. Yet, because α assumes equal item precision—a condition rarely met—recent literature recommends the omega coefficient (ω) as a more accurate alternative [59]. Since ω cannot be computed for scales with fewer than three items or minimal variance, both coefficients were calculated in this study for all the scales (see Table I)

As shown in Table I, the A scale (academic factors), composed of six items, demonstrated good internal consistency ($\alpha = 0.836$, $\omega = 0.833$) and was retained without modification in the final version.

The TA scale (ease of access), with $\alpha = 0.796$ and $\omega = 0.800$, also showed acceptable reliability and remained unchanged. In contrast, the TD scale (perceived difficulty of detection), initially composed of four items, exhibited very low internal consistency. Due to the theoretical relevance of this dimension, the scale was replaced with a single reversed item (TD4), which the authors judged to best capture the construct.

The UR scale (clarity of university regulations) showed adequate internal consistency ($\alpha = 0.778$) and was retained unchanged; omega was not computed as it comprises only two items. The UP dimension (severity of institutional punishment) consists of a single item, which was also retained.

For the ES scale (subjective norm), initially comprising seven items, both alpha and omega coefficients were below acceptable thresholds. Following item-level analysis, ES7—identified as the item with the lowest corrected item-total correlation ($rit < 0.2$) and the highest corrected homogeneity index (IHc) if removed—was discarded [60]. The resulting six-item scale reached $\alpha = 0.619$ and $\omega = 0.616$, still below the 0.70 threshold. Given the limited reliability and the overall length of the questionnaire, the authors decided to exclude the full scale and retain only ES5, the item most representative of subjective norms, specifically peer behavior related to GenAI use.

Similarly, the IK scale (knowledge about plagiarism), initially containing five items, showed low internal consistency ($\alpha < 0.7$). It was replaced by two items: IK1 (subjective knowledge) and IK2 (perceived training needs), based on relevance in the literature.

A comparable issue was observed with the IS scale (perceived self-efficacy), which led to the retention of its two items (IS1 and IS2), but warranted treating them independently rather than as a unified scale.

The decision to retain these items was made to preserve theoretically relevant dimensions without treating unreliable item sets as validated scales. Aspects such as difficulty of detection, subjective norms, knowledge about plagiarism, training needs, and perceived self-efficacy have been consistently considered relevant factors in models explaining attitudes and intentions toward dishonest academic behaviors. However, in the present data, the corresponding multiitem scales did not show sufficient internal consistency to support their use as latent constructs. Therefore, the most conceptually representative items were retained as standalone indicators: TD4 for difficulty of detection, ES5 for peer-related subjective norms, IK1 and IK2 for subjective knowledge and perceived training needs, and IS1 and IS2 for perceived self-efficacy. This strategy allowed these theoretically meaningful dimensions to remain represented in the questionnaire while avoiding the inclusion of psychometrically weak scales. Accordingly, these items should be interpreted as exploratory predictors rather than as validated latent constructs, and future research should refine and expand them into reliable multiitem measures.

[2]The participant information sheet is available at https://bit.ly/hoja_partic

Regarding the five personality scales, Table I shows how the Extraversion (eightitems; $\alpha = 0.778$, $\omega = 0.776$) and Neuroticism (eightitems; $\alpha = 0.781$, $\omega = 0.775$) scales demonstrated acceptable internal consistency. However, the remaining Big Five scales initially fell below the reliability threshold of 0.70. To improve reliability and reduce questionnaire length, items with item-total correlations below 0.2 and high corrected homogeneity indices were removed. For Agreeableness, items 2, 12, 27, and 37 were excluded, resulting in a five-item scale with improved reliability ($\alpha = 0.742$, $\omega = 0.742$). Similarly, Conscientiousness was reduced to five items after removing items 8, 18, 23, and 43, yielding $\alpha = 0.764$ and $\omega = 0.766$. Three items (35, 41, and 44) were removed from the Openness scale, increasing its reliability to $\alpha = 0.814$ and $\omega = 0.815$.

Finally, both attitude scales—DP and DN—showed excellent internal consistency, with α and ω values exceeding 0.90. They were therefore retained for further exploratory factor analysis.

A. Exploratory Factor Analysis of Attitude Scales

From all the scales included in PlagiAct-V2, the two attitude-related scales—DP and DN—warranted further examination. Although both were originally validated by Farooq and Sultana [17] as unidimensional constructs, in this study, we expanded each with additional items designed to enhance GenAI coverage. Therefore, an with EFA) with principal axis factoring (PAF) and promax rotation [61] was conducted to explore whether, within the context of Spanish engineering students, new latent dimensions could be identified, potentially reflecting more specific subcomponents of positive and negative attitudes toward plagiarism.

1) Exploratory Factor Analysis of the DP Scale Dimensions: The first step in the exploratory factor analysis exploratory factor analysis (EFA) was to assess sampling adequacy and factorability using the KMO measure and Bartlett's test [62]. The DP scale yielded a KMO value of 0.917, indicating excellent sampling adequacy for conducting Exploratory Factor Analysis EFA [63]. In addition, Bartlett's test of sphericity was statistically significant ($p < 0.05$), indicating that the correlation matrix differed significantly from an identity matrix and supporting the suitability of the data for factor analysis [64].

Factor retention was assessed using several complementary criteria. According to the Kaiser criterion, five factors presented initial eigenvalues greater than 1. These five factors jointly accounted for 58.585% of the total variance based on the initial eigenvalues. Specifically, the first factor showed an eigenvalue of 8.784 and accounted for 33.786% of the variance; the second, 2.841 and 10.927%; the third, 1.380 and 5.307%; the fourth, 1.161 and 4.464%; and the fifth, 1.066 and 4.101%. After extraction, the retained five-factor solution accounted for 49.647% of the total variance. This five-factor structure was further supported by inspection of the scree plot and by parallel analysis, both of which converged in recommending the retention of five factors (see [55, Appendix E]). The resulting five-factor solution is presented in the structure matrix (Table II), where only absolute loadings equal to or greater than 0.40 are reported to facilitate interpretation [65]. Because an oblique rotation was used, both the structure matrix and the rotated pattern matrix were examined. The structure matrix was used to support the substantive interpretation of the retained factors and the assignment of items to their most meaningful latent dimension, whereas the pattern matrix was used to evaluate the distinctiveness of item loadings and to identify problematic cross-loadings (see [55, Appendix E]). Item retention was first assessed from the structure matrix reported in Table II, as this matrix provides the basis for the substantive interpretation of the factor solution. Items DP1, DP5, DP8, and DP11 were removed because they did not show any salient loading in the structure matrix, indicating no clear association with any retained factor. For items that did show salient associations in the structure matrix but remained problematic, the rotated pattern matrix and communalities reported in [55, Appendix E] were examined as complementary evidence. DP12 showed a salient association with Factor PL in the structure matrix, but its corresponding pattern loading did not reach the 0.40 threshold (see [55, Appendix E]), suggesting that this association was not sufficiently clear once the correlations among factors were taken into account. DP16 also appeared in the structure matrix, but with similarly salient associations with more than one factor, indicating an ambiguous factorial assignment; moreover, it did not show a clear salient loading in the pattern matrix. Therefore, DP12 and DP16 were also excluded. Overall, these exclusions contributed to a cleaner and more interpretable internal structure, while also reducing the length of the questionnaire.

After exclusions, reliability was reassessed for the full scale and subscales; Table III reports the subscale names, final item counts, item lists, Cronbach's alpha, and McDonald's omega for each dimension.

2) Exploratory Analysis of the DN Scale Dimensions: The exploratory factor analysis EFA on the DN scale showed excellent sampling adequacy (KMO=0.915) and a significant Bartlett's test ($p<0.05$), confirming suitability for factor analysis.

For the DN scale, factor retention was again assessed using several complementary criteria. According to the Kaiser criterion, four factors presented initial eigenvalues greater than 1, jointly accounting for 60.857% of the total variance. Specifically, Factor 1 showed an eigenvalue of 7.486 and explained 37.432% of the variance; Factor 2, 2.014 and 10.072%; Factor 3, 1.495 and 7.474%; and Factor 4, 1.176 and 5.878%. After extraction, the retained four-factor solution accounted for 51.099% of the total variance. This structure was further supported by inspection of the scree plot, and by parallel analysis, both reported in [55, Appendix F].

Because an oblique rotation was used, both the structure matrix (see Table IV) and the pattern matrix and communalities table (reported in [55, Appendix F]) were examined. This analysis identified DN6, DN18, and DN20 as problematic items. DN6 showed correlations above 0.40 with several factors in the structure matrix, but no salient loading in the pattern matrix, suggesting a diffuse rather than specific factorial association. DN18 also lacked a salient pattern loading and showed low extracted communality, indicating weak representation in the retained factor solution. DN20 reached

TABLE II

EFA DN: STRUCTURE MATRIX. LI: LEARNING IMPAIRMENT. P: PUNISHMENT. E: ETHICS. R: RISKS. ITEMS MARKED WITH AN ASTERISK (*) INDICATE PROBLEMATIC ITEMS THAT WERE EXCLUDED FROM THE FINAL VERSION OF THE QUESTIONNAIRE AFTER THE EFA

ID	Item	Component				
		PC	Ut	WS	EU	PL
DP1*	DP1. Sometimes in academic papers you can't avoid using ChatGPT, because the number of ways you can describe something is limited.					
DP2	DP2. In academic papers it is justified to use ChatGPT to comment on general topics, concepts, theories, methods, etc. without citation, precisely because the topic is generic.			0.701		
DP3	DP3. If I cannot write well on a topic because I am unfamiliar with it, I am justified in using ChatGPT to express ideas appropriately.			0.678		
DP4	DP4. The use of ChatGPT can be overlooked if the result is high quality work.	0.573		0.605		
DP5*	DP5. Punishment for unauthorised use of ChatGPT at university should be light, because we are young people who are learning.					
DP6	DP6. The use of ChatGPT to perform an academic task or an important part of it is not serious, as we are not stealing other people's ideas or words, but they have been generated in a completely original way by ChatGPT.	0.723		0.562		
DP7	DP7. When I don't know what to write, using ChatGPT to generate content or translate content from another language is acceptable.			0.623		
DP8*	DP8. It is not dishonest to use ChatGPT to generate a few paragraphs for inspiration on a piece of work.					
DP9	DP9. The use of ChatGPT is not punishable because it does not harm anyone (you cannot steal a text that is currently being generated).	0.732		0.585		
DP10	DP10. It is justified to use ChatGPT without citation to complete any work: plagiarism of ChatGPT makes no sense.	0.786		0.602		
DP11*	DP11. The use of ChatGPT should not be punished in the same way that plagiarism is punished.					
DP12*	DP12. I don't feel guilty for copying verbatim a paragraph or two from ChatGPT.					0.553
DP13	DP13. Using ChatGPT is justified if it allows you to get better grades.	0.600				0.619
DP14	DP14. Using ChatGPT is justified if it saves time when performing assigned tasks.			0.568		0.660
DP15	DP15. Since ChatGPT is in the public domain, copying content generated by it does not require citing or acknowledging the source.	0.717		0.554		
DP16*	DP16. The use of ChatGPT does NOT undermine the value of my undergraduate studies (the preparation they give me for the world of work).	0.545	0.524			
DP17	DP17. I do not feel guilty for directly presenting the output generated by ChatGPT as my work because I am the one who has designed and introduced the necessary prompt to obtain the output.	0.729				
DP18	DP18. I consider that copying verbatim one or two paragraphs from ChatGPT is NOT unlawful or unethical behaviour in my academic work.			0.509		0.654
DP19	DP19. I consider that presenting as my work the result generated by ChatGPT is NOT an illegal or unethical behaviour in my academic work, because I am the one who has designed and introduced the necessary prompt to obtain that result.	0.702				
DP20	DP20. I am excited about the possibilities that ChatGPT offers for my learning.		0.797			
DP21	DP21. I believe ChatGPT is an important tool for academic success.		0.735			
DP22	DP22. I think ChatGPT is attractive and fun to use.		0.789			
DP23	DP23. I find that using ChatGPT saves me time and work effort without detracting from my learning.		0.731			
DP24	DP24. I find ChatGPT more useful than other sources of information I have used in the past.		0.654			
DP25	DP25. Learning to use ChatGPT does not take long.				0.823	
DP26	DP26. Learning to use ChatGPT does not require advanced technical knowledge.				0.729	

TABLE III

RELIABILITY OF DN SUB-DIMENSIONS

Dim	#I	Items	Alpha	Omega
Perceived content ownership	6	DP6, DP9, DP10, DP15, DP17, DP19	0.870	0.867
Utility	5	DP20, DP21, DP22, DP23, DP24	0.856	0.857
Writing Support	4	DP2, DP3, DP4, DP7	0.749	0.751
Perceived legitimacy	3	DP13, DP14, DP18	0.757	0.760
Ease of use	2	DP25, DP26	0.778	-
DP	20	All	0.904	0.898

the minimum threshold of 0.40 on the Risk factor in the pattern matrix, but its very low communality indicated insufficient shared variance with the overall structure. Consequently, DN6, DN18, and DN20 were removed to obtain a cleaner and more interpretable solution and to reduce questionnaire length.

A further decision concerned the Risks factor. The items initially associated with this factor showed comparatively weak psychometric behavior, with salient pattern loadings close to the minimum threshold, particularly for DN4 and DN20. After removing DN18 and DN20, the Risk factor was reduced to only two items, DN4 and DN19. Although two-item factors may sometimes be retained when theoretically strong and empirically consistent, this was not the case here. As shown in Table V, the reliability analysis of the two remaining Risk items yielded a clearly inadequate internal consistency coefficient (Cronbach's $\alpha = 0.458$), providing insufficient support for retaining Risks as a stable and psychometrically robust dimension. Accordingly, the Risk factor was excluded from the final questionnaire.

TABLE IV

EFA DN: STRUCTURE MATRIX. LI: LEARNING IMPAIRMENT. P: PUNISHMENT. E: ETHICS. R: RISKS. ITEMS MARKED WITH AN ASTERISK (*) INDICATE PROBLEMATIC ITEMS THAT WERE EXCLUDED FROM THE FINAL VERSION OF THE QUESTIONNAIRE AFTER THE EFA

	Item	LI	P	E	R
DN1	DN1. Using ChatGPT to complete my academic assignments is against my ethical values.	0.464		0.692	
DN2	DN2. I would not feel comfortable if my classmates were using ChatGPT to complete their academic assignments.	0.462	0.497	0.749	
DN3	DN3. I believe that using ChatGPT for academic assignments provides an unfair advantage over students who do not.	0.428		0.680	
DN4*	DN4. Given the perceived moral decline in moral and ethical standards, it is important to discuss the use of ChatGPT in class.				0.473
DN5	DN5. Using ChatGPT to complete academic tasks takes away the opportunity to learn and improve my skills.	0.698		0.593	
DN6*	DN6. Using ChatGPT is as bad as stealing the wording of an exam paper.	0.522	0.580	0.577	
DN7	DN7. The use of ChatGPT impoverishes the university spirit.	0.747	0.503	0.677	
DN8	DN8. Those who use ChatGPT illicitly should not be at university.		0.736	0.411	
DN9	DN9. I think I should be punished if I am found to have used ChatGPT to perform a complete task or a major part of it and presented it as if it were my own work.		0.590		
DN10	DN10. I believe that the ChatGPT user lacks academic integrity.	0.693	0.632	0.680	
DN11	DN11. If it is proven that a student has used ChatGPT illegally in any subject, this fact should appear on the student's transcript.		0.762		
DN12	DN12. I believe that using ChatGPT to carry out my academic tasks would negatively affect the quality of the training received during my university studies.	0.809	0.457	0.577	
DN13	DN13. I believe that, when unauthorised use of ChatGPT is detected, severe measures should be applied at the university.	0.410	0.697	0.409	
DN14	DN14. The names of students who use ChatGPT and pass it off as their own work should be disclosed to the university community.		0.677		
DN15	DN15. Using ChatGPT impairs independent thinking.	0.763			0.414
DN16	DN16. Using ChatGPT harms the development of my critical thinking skills.	0.856		0.453	
DN17	DN17. I believe that using ChatGPT would lead to a lack of originality in my academic work.	0.733	0.408	0.500	0.473
DN18*	DN18. I am concerned about the potential privacy and security risks I might incur if I use ChatGPT.	0.402			0.472
DN19*	DN19. I worry about becoming too dependent on technologies like ChatGPT.	0.411			0.590
DN20*	DN20. I am concerned about the reliability and accuracy of the information provided by ChatGPT.				0.424

TABLE V

EFA DN: STRUCTURE MATRIX. LI: LEARNING IMPAIRMENT. P: PUNISHMENT. E: ETHICS. R: RISKS. ITEMS MARKED WITH AN ASTERISK (*) INDICATE PROBLEMATIC ITEMS THAT WERE EXCLUDED FROM THE FINAL VERSION OF THE QUESTIONNAIRE AFTER THE EFA

Dim	**#I**	**Items**	**Alpha**	**Omega**
Learning Impairment	7	DN5, DN7, DN10, DN12, DN15, DN16, DN17	0.903	0.903
Punishment	5	DN8, DN9, DN11, DN13, DN14	0.820	0.819
Ethics	3	DN1, DN2, DN3	0.757	0.757
DN	15	All	0.900	0.904

Following these exclusions, reliability was re-assessed for the full DN scale and each subdimension. Table V presents the subscale names, final item counts, item lists, Cronbach's alpha, and McDonald's omega coefficients.

The outcomes of the reliability and validity analyses led to the final definition of the PlagiAct-V3 instrument—the main contribution of this study—which is summarized in [55, Appendix F]. The results provide evidence supporting content validity and acceptable internal consistency reliability for the retained scales. In addition, the exploratory factor analyses offer preliminary support for interpretable latent structures in the DP and DN attitude scales.

V. DISCUSSION

In PlagiAct, the dimensions defined in the conceptual model—personal, academic, institutional, technological, and external—are theoretically grounded components of a broader explanatory model of AI-giarism. This alignment was established by design, linking each dimension to mechanisms derived from Merton's strain theory of anomie, Lazarus and Folkman's stress and coping theory, Kahneman and Tversky's prospect theory, and Ajzen's theory of planned behavior. This theoretical alignment gives practical meaning to the scores obtained in each dimension. Rather than merely describing students' opinions, these scores may indicate mechanisms that increase or reduce vulnerability to plagiarism-related behaviors. For example, a low score on the academic factors dimension may suggest that students perceive academic tasks as excessively demanding, poorly aligned with their resources, insufficiently meaningful, or weakly connected to learning. From the theoretical model, this may indicate increased strain, academic stress, and a greater likelihood of accepting GenAI-assisted shortcuts as a response to academic pressure. Such scores should not be interpreted as evidence of misconduct, but as risk indicators that can guide preventive action. Accordingly, PlagiAct factor scores can support targeted interventions. For example, in the case of low scores on academic factors, instructors may redesign assignments to make their learning purpose explicit, provide intermediate milestones and formative feedback, clarify acceptable and unacceptable uses of GenAI, reduce ambiguity in task requirements, and require students to document and justify their own contribution.

The identification of subdimensions within the DP and DN scales further strengthens this diagnostic value. The exploratory factor analysis (EFA) results suggest that attitudes toward AI-giarism are not homogeneous constructs. In the

DP scale, the subdimensions relate to content ownership, perceived utility, writing support, perceived legitimacy, and ease of use of GenAI tools. In the DN scale, they relate to perceived learning impairment, punishment, and ethical concerns. Thus, similar overall scores may reflect different attitudinal profiles and require different responses. This multidimensional structure has direct implications for intervention design. If students perceive generated content as their own, interventions should focus on authorship, intellectual ownership, and attribution. If perceived utility or writing support is high, instructors should clarify the boundary between acceptable assistance and substitution of intellectual work. If perceived legitimacy is high, institutional and course-level expectations should be made explicit through examples of acceptable, questionable, and unacceptable uses. If ease of use is a relevant driver, assessment design should incorporate process evidence, intermediate drafts, oral explanations, reflective logs, or task-specific justification of decisions. Similarly, low concern about learning impairment, punishment, or ethics may indicate the need to address, respectively, the learning costs of inappropriate use, the clarity and credibility of institutional consequences, or students' ethical reasoning. However, these subdimensions are based on exploratory factor analyses and should be interpreted as preliminary evidence of internal structure. Future studies should confirm this structure using confirmatory factor analysis and examine its stability across samples, degrees, and institutional contexts.

A. Main Contributions and Practical Implications

This study makes three main contributions. First, it proposes a conceptual framework for explaining plagiarism and AI-giarism as multifactorial phenomena, grounded in the literature and mapped to four established theories: Merton's strain theory, Lazarus and Folkman's stress and coping theory, Kahneman and Tversky's prospect theory, and Ajzen's theory of planned behavior.

Second, it introduces PlagiAct-V3, an instrument that addresses key gaps in existing tools by combining theoretical grounding, psychometric exploration with a large engineering sample, and applicability to STEM and European higher education contexts. Unlike instruments focused only on attitudes, PlagiAct-V3 also measures individual, academic, technological, external, and institutional drivers, making it a diagnostic tool for the GenAI era. A pilot correlational analysis showing which factors are more strongly associated with attitudes in the study sample is provided in [55]].

Third, the study empirically identifies the multidimensional structure of positive and negative attitudes toward AI-giarism, enabling more nuanced and context-sensitive pedagogical and institutional responses.

In summary, PlagiAct-V3 enables institutions to move beyond generic academic integrity policies toward evidence-based and context-sensitive interventions integrating pedagogy, governance, and technology.

B. Threats to Validity

This study considered threats to construct, internal, and external validity. Regarding construct validity, transforming complex constructs into concise questionnaire items is inherently difficult [66]. To mitigate this threat, PlagiAct-V3 integrates items from validated scales [15], [16], [17], expert review, and student pretests. However, some cultural or technological nuances may remain underrepresented. In addition, reliance on self-reports may introduce recall errors [67] and social desirability bias [68], although reduced through anonymity and voluntary participation, cannot be fully eliminated.

Regarding internal validity, some items were removed to improve reliability and internal structure, which may have reduced construct depth in dimensions such as subjective norms or self-efficacy. Some constructs were also measured with few or single items, limiting sensitivity. Nevertheless, reliability and factor analyses were used to retain the most representative items and avoid psychometrically weak scales.

Regarding external validity, the validation was conducted in Spanish on-site universities with a relatively homogeneous sample of engineering students selected through convenience sampling. Therefore, generalization to online, international, non-STEM, or more diverse educational contexts should be made with caution. Given the rapid evolution of attitudes toward plagiarism and GenAI, periodic revalidation and replication studies are needed.

C. Future Work

Future research involves applying the PlagiAct-V3 instrument in diverse cultural, disciplinary, and institutional contexts to assess its generalizability and confirm the factor structure identified here through confirmatory factor analysis using independent samples.

Another important avenue for future work involves developing individual indicators into multiitem scales to enable more robust reliability and construct validation analyses. Also, the inclusion of established social desirability inventories [69] would help to quantify the extent to which social desirability influences participants' responses. This would allow for more nuanced interpretations of the data, and ultimately enhance the robustness of the conclusions.

The relevance and impact of AI-giarism in education is underscored by the number of new instruments proposed since the inception of PlagiAct. Although their limitations have already been discussed, these tools offer valuable insights that merit closer examination. Future work will explore which of these approaches may inform a potential evolution and re-validation of PlagiAct, allowing the incorporation of new perspectives and constructs to further enrich its framework.

With PlagiAct-V3, we aim to examine how institutional interventions (e.g., integrity training, GenAI literacy, policies) influence student attitudes and behaviors over time. Longitudinal studies could track shifts and strategy effectiveness.

Finally, a key inquiry is the alignment between self-reported attitudes and actual behaviors. It is important to test whether permissive attitudes toward uncredited GenAI use predict such practices, and how situational factors (e.g., deadlines, perceived risk) shape plagiarism behavior.

VI. Conclusion

This study developed PlagiAct-V3, a theoretically grounded instrument for assessing factors and attitudes related to plagiarism and AI-giarism in higher education. The instrument is based on a conceptual model informed by Merton's strain theory, Lazarus and Folkman's stress and coping theory, Kahneman and Tversky's prospect theory, and Ajzen's theory of planned behavior. These theoretical foundations are operationalized through five domains: personal, academic, institutional, technological, and external factors.

The reliability analyses provided evidence of adequate internal consistency for the retained scales, while the exploratory factor analyses offered preliminary support for the internal structure of the attitude scales among engineering students. Specifically, DP was organized into five subdimensions: content ownership, perceived utility, perceived writing support, perceived legitimacy, and ease of use of GenAI tools. DN was organized into three subdimensions: perceived learning impairment, punishment, and ethical concerns.

These findings support the multidimensional nature of attitudes toward plagiarism and AI-giarism. Rather than treating such attitudes as a single favorable or unfavorable position, PlagiAct-V3 helps identify the specific mechanisms that may shape students' perceptions, such as perceived authorship, instrumental usefulness, legitimacy, ease of use, learning consequences, institutional sanctions, and ethical concerns. This diagnostic capacity makes the instrument useful not only for research, but also for designing targeted educational and institutional interventions to foster academic integrity in the GenAI era.

Future studies should confirm the proposed structure through confirmatory factor analysis, examine its stability across disciplines, institutions, and cultural contexts, and assess the instrument's sensitivity to changes in students' attitudes as GenAI tools and academic integrity policies continue to evolve.

Data Availability Statement

The data that support the findings of this study are available on Zenodo in SPSS format (.sav) at https://bit.ly/PlagiActV3-DataSet, with reference number 10.5281/zenodo.15014276.

Competing Interests

The authors declare no competing interests.

Use of GenAI

ChatGPT (GPT 5.4) was used to improve the writing quality of this article. Spanish text was translated into English with the prompt "Translate this paragraph into English," while English text was refined with the prompt "Improve the English of this paragraph while maintaining the integrity of the content." All outputs were reviewed and edited by the authors, who take full responsibility for the content.

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