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Ethics and regulation of AI in higher education: a comparative study of spanish and romanian students using SEM

Ética y regulación de la IA en la educación superior: un estudio comparativo de alumnado español y rumano usando el modelo SEM

Raluca Stoica[1], Laura Díaz-Reyes[2], Diego Acosta-Gijón[3], Jesús Heredia-Carroza[3]

[1] Alexandru Ioan Cuza University of Iasi, Romania
[2] Universidad CEU Fernando III, CEU Universities, Spain
[3] Universidad de Sevilla, Spain

raluca.stoica@feaa.uaic.ro , ldiaz@ceu.es , dieacogij@alum.us.es , jheredia1@us.es

ABSTRACT. This study uses Structural Equation Modelling (SEM) to examine ethical and regulatory perceptions of artificial intelligence in higher education among 364 university students (116 Romanian, 248 Spanish). Results reveal significant cross-national differences, emphasising the role of culture in ethical attitudes. While AI performance showed no significant impact, regulation emerged as a key predictor of ethical acceptance. Findings highlight students' preference for clear regulatory frameworks over technological efficiency. The study supports culturally responsive policies and calls for governance models that ensure equitable, transparent, and accountable AI integration in academic contexts.

RESUMEN. Este estudio utiliza el Modelado de Ecuaciones Estructurales (SEM) para examinar las percepciones éticas y regulatorias de la inteligencia artificial en la educación superior de 364 estudiantes universitarios (116 rumanos, 248 españoles). Los resultados arrojan luz sobre importantes diferencias transnacionales, destacando el papel de la cultura en las actitudes éticas. Si bien el rendimiento de la IA no mostró un impacto significativo, la regulación se posicionó como un predictor clave de la aceptación ética. Los hallazgos resaltan la preferencia de los estudiantes por marcos regulatorios claros sobre la eficiencia tecnológica. El estudio apoya políticas culturalmente receptivas y aboga por modelos de gobernanza que garanticen una integración equitativa, transparente y responsable de la IA en contextos académicos.

KEYWORDS: Artificial Intelligence, Ethics, Regulation, Higher Education, Cultural differences.

PALABRAS CLAVE: Inteligencia Artificial, Ética, Regulaciones, Educación Superior, Diferencias culturales.

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1. Introduction

The integration of artificial intelligence (AI) into higher education has generated both transformative opportunities and significant challenges, particularly in the ethical and regulatory domains. As AI technologies become increasingly prevalent in academic environments - from automated grading and personalised learning to research support systems - the urgency to evaluate their ethical implications has grown. In this context, it is crucial to understand how students perceive AI in terms of ethical standards, regulatory needs, and institutional governance.

Prior studies have addressed AI's pedagogical potential and technical applications in academia (Chauke et al., 2024; Lin, 2023). However, fewer research has explored the intersection of performance perception, cultural influences, and the demand for ethical regulation. This paper fills that gap by applying Structural Equation Modelling (SEM) to analyse the perceptions of 364 students (116 Romanian and 248 Spanish) concerning the ethical use and regulation of AI in higher education.

This study highlights that students' ethical perceptions of AI are influenced more by the existence of regulatory safeguards than by the perceived technical efficacy of AI. In particular, cultural background is hypothesised to be a moderating factor in how students evaluate ethical concerns. The constructs of Performance and Regulation are assessed for their impact on ethical perception, using SEM to establish relationships and differences across national contexts.

This paper aims to contribute to the debate by examining how regulation and perceived performance influence students' ethical views of AI across two national contexts.

2. Theoretical framework and literature review

2.1. Ethics and Regulation of AI in Higher Education

The governance of AI in education has become a critical concern due to its implications for transparency, fairness, and social inclusion. Regulatory frameworks aim to address these issues but vary widely in their models and effectiveness. Table 1 outlines key regional approaches to AI regulation, demonstrating divergent strategies based on geopolitical priorities, legal traditions, and cultural values (Almeida et al., 2022; Erdélyi & Goldsmith, 2018; Walter et al., 2024).

Region/Country	Main Regulatory Framework	Regulatory Model	Advantages	Disadvantages
European Union	GDPR, AI Act (Almeida *et al.*, 2022)	Hard law	Provides legal certainty. Prioritizes individual rights.	May limit technological innovation.
United States	BIPA (Illinois) (Taiwo *et al.*, 2023)	Fragmented (state-level hard law)	Offers flexibility at the state level.	Lacks a coherent federal framework. Exhibits regulatory fragmentation.
China	AI Ethics Code, 2017 Development Plan (Tuzov & Lin, 2024)	Centralized hard law	Enhances global competitiveness.	Lacks mechanisms to enforce ethical principles.
Japan	Society 5.0 (Wright, 2024; Xu *et al.*, 2024)	Soft law	Promotes progressive principles such as human centrality.	Laws enforceability. Lacks diversity in regulatory bodies (13.8% women).
Thailand	Ethical Guidelines in "Thailand 4.0" (Hongladarom, 2021)	Soft law	Offers flexibility to adapt to local values.	Excludes citizen participation. Prioritizes economic interests.
Global Proposal	IAIO (Erdélyi & Goldsmith, 2018)	Hybrid model	Balances flexibility and binding standards.	Requires sovereignty concessions and international cooperation.

Table 1. Regulatory Models and Regional Approaches in AI Governance. Source: Own elaboration.

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European frameworks focus on data protection and accountability but often struggle to keep pace with innovation (Ozga, 2012). Meanwhile, U.S. state-level legislation such as BIOMETRIC Information Privacy Act (BIPA) offers flexibility but lacks cohesion (Erdélyi & Goldsmith, 2018; Camilleri, 2024). In China, regulation is centralised and aligned with national development goals, prioritising societal welfare over individual autonomy (Marginson & Yang, 2022). Japan's soft law model (Society 5.0) emphasises ethical AI but suffers from low enforceability and gender imbalance in governance structures (Wright, 2024; Treude & Hata, 2023).

Furthermore, Latin America and Africa face additional challenges, including limited infrastructure and low female participation in STEM fields, which perpetuate structural inequalities in algorithmic design (Tidjon & Khomh, 2022; Cernadas & Calvo-Iglesias, 2020). These global disparities suggest that effective regulation must consider both technical feasibility and socio-cultural diversity.

Technical tools such as LIME (Local Interpretable Model-Agnostic Explanations) and SHAP (Shapley Additive exPlanations) have been proposed to enhance algorithmic transparency and interpretability (Boch et al., 2022; Pillai, 2024), but their adoption remains inconsistent without binding regulations. Thus, hybrid governance models combining global standards with local adaptation are gaining traction (Zhu, 2024). Other similar initiatives include the "Initiative for AI Audit and Equity" (IAIO), which advocates for diversity quotas in technology development teams (Greene et al., 2023).

2.2. Cross-Cultural Perspectives on AI Governance

Cultural and institutional contexts significantly shape regulatory approaches and ethical interpretations of AI (Lin, 2023; Montgomery, 2023). Western models often emphasise individual rights, market efficiency, and technological autonomy, while Eastern models privilege collective well-being and state-led innovation (Marginson & Yang, 2022; Tuzov & Lin, 2024). For example, Anglo-American education prioritises employability and performance metrics, whereas Chinese and Japanese systems are more attuned to communal development and moral education (Wright, 2024).

The OECD has further influenced global education by promoting digitalisation through future-oriented narratives, which some scholars argue risk marginalising non-Western worldviews (Mertanen & Brunila, 2024; Nemorin, 2024). Initiatives such as UNESCO's digital education strategies may unintentionally reinforce colonial epistemologies, overlooking indigenous knowledge systems and local pedagogical traditions (Akhtar, et al., 2024).

Consequently, calls for pluriversal ethics are gaining ground - frameworks that go beyond Eurocentric values to incorporate perspectives from the Global South and other historically marginalised groups. Such inclusive ethics are crucial for designing AI systems that foster equity and cultural sensitivity in education (Stanford, 2023).

2.3. Gaps in Empirical Research and Hypotheses

While theoretical debates on AI ethics have proliferated, empirical research remains limited in scope and diversity. Most studies concentrate on technical performance or generalised attitudes, often within a single national context (Rasul et al., 2023). There is a pressing need for comparative analyses that integrate cultural dimensions and assess how regulation and perceived utility shape ethical evaluations among students.

To address this gap, the present study formulates the following hypotheses:

Recent literature has suggested that perceived performance of AI systems may influence how individuals assess their ethical value, especially in contexts where efficiency and automation are prioritised. In academic settings, students' exposure to tools such as automated feedback systems or recommendation algorithms could lead them to equate technical reliability with ethical appropriateness. This relationship is particularly relevant in light of studies that warn about the dependence on AI tools like ChatGPT and their potential to compromise

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critical thinking (Wiredu et al., 2024; Chauke et al., 2024).

H1: Students perceive that AI performance positively influences their perception of AI ethics.

AI is increasingly used in academic environments to automate grading, personalize learning, and support decision-making. Students who perceive these systems as reliable and effective may associate such functionality with ethical soundness, interpreting efficiency as a proxy for responsibility. However, evidence suggests that regulation often plays a more central role in shaping ethical trust than performance alone. The European Union's AI Act, for instance, emphasises transparency and accountability over technical prowess (Almeida et al., 2022; Gross, 2023). This hypothesis investigates whether perceived AI performance is nonetheless a significant predictor of ethical evaluation.

H2: Students perceive that AI regulation positively influences their perception of AI ethics.

AI is rapidly transforming higher education practices, from assessment protocols to academic content generation. Students who are more aware of or affected by these changes may be more attuned to potential ethical risks or benefits, thereby developing stronger ethical stances on AI use. Academic integrity remains a top concern among universities adapting to AI, suggesting that perceived transformation can heighten ethical scrutiny (Malik et al., 2023; Jarrah et al., 2023).

H3: Students who perceive greater changes in academia due to AI, also express stronger ethical concerns.

Cultural values and educational traditions vary significantly across countries, affecting how ethical issues are interpreted and prioritised. Comparative research has demonstrated that national regulatory frameworks and sociocultural factors shape students' perceptions of AI, as seen in the divergence between European individual-rights models and collectivist approaches in East Asia (Marginson & Yang, 2022; Wright, 2024).

H4: Nationality influences ethical perceptions of AI.

Some studies have explored the role of gender in ethical reasoning, suggesting that men and women may prioritise different values or concerns when evaluating emerging technologies. Bias in algorithmic outputs—such as gendered stereotypes in hiring and educational platforms—raises the question of whether ethical sensitivities differ by gender (Abdollahi et al., 2024; Cernadas & Calvo-Iglesias, 2020). In AI contexts, this may affect how students interpret bias, accountability, or social impact. Gendered stereotypes embedded in algorithmic outputs - such as those found in hiring and educational platforms - raise the question of whether ethical awareness varies across gender groups (Abdollahi et al., 2024; Cernadas & Calvo-Iglesias, 2020). This hypothesis examines whether these perceptual differences translate into distinct ethical evaluations of AI in education. As an example, technologies like DALL-E 2 underrepresent women in scientific roles while overrepresenting them in caregiving professions (Sun et al., 2024), a trend mirrored in Bing Image Creator, where 80% of STEM-related images feature men (Sandoval-Martin & Martínez-Sanzo, 2024; Buolamwini & Gebru, 2018; Hall & Ellis, 2023).

H5: Students perceive that gender influences ethical perceptions of AI.

Students' awareness of artificial intelligence (AI) significantly shapes their ethical perceptions regarding its use in educational and professional environments. The more students understand the principles, capabilities, and limitations of AI, the more likely they are to identify ethical challenges such as bias, privacy violations, and accountability gaps. According to Jobin et al. (2019), the development of global AI ethics guidelines highlights the crucial role that knowledge and education play in fostering critical awareness of these ethical issues. Therefore, promoting AI literacy is essential to empower students to evaluate AI applications responsibly and contribute to ethical technology development and use.

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H6: Students perceive that knowledge of AI influences ethical perceptions.

By employing SEM to evaluate these hypotheses, our research aims to provide a robust empirical foundation for understanding how regulatory frameworks and performance expectations influence ethical perceptions in higher education across cultural boundaries.

3. Method

3.1. Participants

A total of 364 undergraduate students participated in the study. The sample was composed of 116 Romanian students and 248 Spanish students enrolled in various social sciences programmes. The age of the participants ranged from 18 to 30 years. Based on gender distribution, 60.2% identified as female and 39.8% as male, as shown in Table 2. The survey was administered online during March 2024 via institutional platforms and university mailing lists. Participation was voluntary, anonymous, and preceded by informed consent. The survey was optimised for mobile and desktop use, and the average completion time was approximately 10 to 15 minutes.

Variable	Categories	N	%
Nationality	Spanish	248	68.1%
	Romanian	116	31.9%
Gender	Female	219	60.2%
	Male	145	39.8%

Table 2. Descriptive Statistics of the Sample. Source: Own elaboration.

3.2. Materials and procedure

The study employed a structured online questionnaire designed to measure university students' perceptions of artificial intelligence in higher education. The instrument was developed in English and validated by a panel of academic experts in both Romania and Spain to ensure cross-cultural clarity and linguistic consistency. The survey consisted of three key sections: socio-demographic characteristics, self-perceived AI knowledge, and attitudes towards AI performance, regulation, ethical implications, and its perceived impact on higher education.

The first section included questions on gender, nationality, age group, and educational background. Importantly, it also assessed students' self-reported level of knowledge regarding AI, measured on a 7-point Likert scale ranging from 1 (Very Low) to 7 (Very High). These values were recoded to a standardised 7-point scale to ensure compatibility with other variables in the analysis.

The second section focused on students' direct perceptions of AI in academic environments. Items related to AI performance included statements such as "AI helps me improve my academic performance" and "AI increases my productivity," evaluated on a 7-point Likert scale (1 = Strongly Disagree, 7 = Strongly Agree). This section also captured students' perception of changes in academia due to AI, with items like "AI will change the academic process in the near future".

The third section addressed ethical concerns and regulatory views. Perceptions of AI ethics were measured through Likert-scale items addressing fairness, transparency, and moral responsibility in AI usage. Students' views on the need for regulation were assessed using two dichotomous (yes/no) items. Specifically, students were asked: (1) whether AI in higher education should be regulated by European law, and (2) whether a global agreement is needed to govern AI use in academia. These two binary variables were included in the analysis as categorical indicators reflecting regulatory awareness and support, asking whether they believed AI in higher education should be regulated by European law and whether a global agreement is needed to govern AI use in academia.

Variable	N	Mean	SD	Min	Max
AI Performance – Answer Quality (P1)	364	4.77	1.45	1	7
AI Performance – Improve Work (P2)	364	4.65	1.58	1	7
AI Performance – Productivity (P3)	364	4.76	1.69	1	7
AI Perceived Change in Academia	364	4.74	1.68	1	7
Regulation – Need for Rules (R1)	364	0.83	0.37	0	1
Regulation – Global Agreement (R2)	364	0.76	0.43	0	1
Knowledge of AI Level	364	3.99	1.30	1	7

Table 3. Statistics Descriptives of the variables measured. Source: Own elaboration.

3.3. Measurement of Variables

The main constructs were operationalized based on validated scales and adapted to the context of AI in higher education. Internal consistency and construct validity were evaluated using Cronbach's alpha (α), Composite Reliability (CR), Average Variance Extracted (AVE), and the Heterotrait-Monotrait ratio (HTMT), following standard recommendations in SEM literature (Hair et al., 2010; Solakis et al., 2021).

Table 3 presents the results of the measurement model. Both the performance and regulation constructs exceeded the acceptable thresholds for internal consistency (α > 0.70), convergent validity (AVE > 0.50), and composite reliability (CR > 0.70). The performance construct yielded α = 0.7588, AVE = 0.524, and CR = 0.765, while regulation scored α = 0.8132, AVE = 0.697, and CR = 0.821, supporting the robustness of the scale. Table 4 shows acceptable internal consistency and convergent validity for both constructs, with CR values above 0.7 and AVE values at or above the 0.5 threshold. All item loadings exceed 0.6, supporting the reliability of the measurement model.

SEM-Measurement Model

Constructs	Codes	⅄	α	AVE	CR
Performance			0.7588	0.52	0.762
	P1	0.607			
	P2	0.821			
	P3	0.728			
Regulation			0.8132	0.696	0.821
	R1	0.782			
	R2	0.885			

Note: ⅄=Loadings; a=Cronbach's Alpha Coefficient; AVE= Average Variance Extracted; CR= Composite Reliability

Table 4. SEM-Measurement Model. Source: Own elaboration.

Discriminant validity was verified. Table 5 shows that the square root of AVE for each construct (in bold on the diagonal) is greater than the inter-construct correlations, confirming discriminant validity. Furthermore, the correlation between performance and regulation was significant ($r = 0.000$, $p < 0.001$).

SEM's discriminant validity

Construct	Performance	Regulation
Performance	**0.724**	
Regulation	0.000**	**0.835**

Note: The bold figures are the square root of the AVE. The normal figures are correlation between variables.
**Significant at the 0.001 level (2-tailed).
SPSS v.22.

Table 5. SEM's discriminant validity. Source: Own elaboration.

Complementarily, the HTMT ratio was employed to test discriminant validity more rigorously (Gaskin & James, 2019). The HTMT value between the constructs was 0.076, see Table 6, far below the recommended threshold of 0.85, confirming that the constructs are empirically distinct.

HTMT Analysis

Construct	Performance	Regulation
Performance		
Regulation	0.076	

Table 6. HTMT Analysis. Source: Own elaboration.

Finally, to assess the presence of Common Method Bias (CMB), we conducted the Specific Bias Test (SBT), a more robust alternative to Harman's single-factor test (Podsakoff et al., 2003). This method, developed by Gaskin and Lim (2017), compares a restricted and unrestricted model to test for latent method effects. As shown in Table 7, the chi-square values for both models were identical ($\chi^2 = 23.000$, $df = 733$), with no delta in chi-square and a p-value of 1.000, suggesting no presence of method bias.

Specific Bias Test:	X²	DF	Delta	pvalue
Unconstrained Model	23.000	733	X2=0.000	1
Zero Constrained Model	23.000	733	DF = 0	

Table 7. Specific Bias Test. Source: Own elaboration.

These results validate the psychometric properties of the constructs and confirm the absence of common method variance. The application of these criteria aligns with methodological standards proposed by Lowry and Gaskin (2014) and reflects practices adopted in comparable studies (Heredia-Carroza et al., 2025).

4. Results

The results of the Structural Equation Modelling (SEM) confirm the reliability and validity of the proposed model and highlight several significant relationships among latent constructs and control variables. Figure 1 summarises the proposed structural model, including the six hypotheses tested through SEM. The diagram presents AI Ethics as the endogenous construct and incorporates the predictive paths from performance, regulation, perceived academic impact, nationality, gender, and knowledge level. Each path is labelled with its corresponding hypothesis (H1–H6), allowing a clear visual representation of the relationships evaluated in the empirical analysis.

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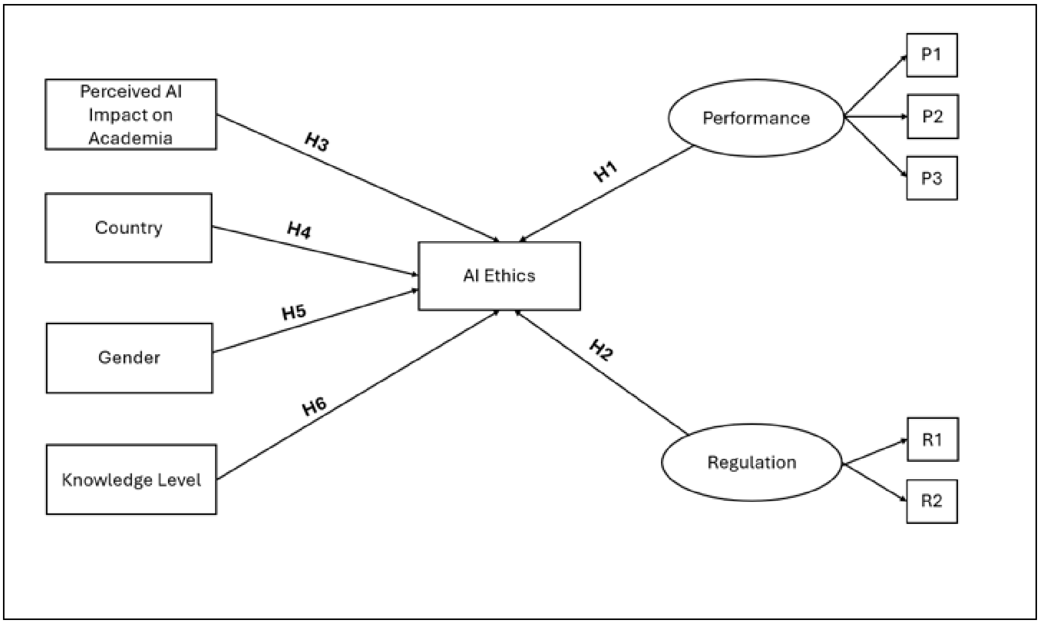

Figure 1. Structural Equation Model and Hypotheses (H1–H6). Source: Own elaboration.

The model demonstrates a satisfactory global fit. As shown in Table 8, all indices fall within the recommended thresholds: $\chi^2(33) = 62.289$, $\chi^2/df = 1.888$, GFI = 0.968, AGFI = 0.947, CFI = 0.958, IFI = 0.959, TLI = 0.943, NFI = 0.916, and RMSEA = 0.049. These indices confirm a good fit and support the adequacy of the measurement and structural model (Hair et al., 2010; Heredia-Carroza et al., 2025).

Hypotheses	N=364				
	Estimate	**S.E.**	**C.R.**	**p**	**R2**
Performance → ai_ethics	0.080	0.123	1.266		
Regulation→ ai_ethics	0.202	0.316	3.714	***	
ai_change_academia→ ai_ethics	0.346	0.057	6.133	***	
Country→ ai_ethics	0.131	0.175	2.721	**	
Gender → ai_ethics	0.004	0.165	0.075		
Knowledge_level → ai_ethics	-0.013	0.063	-0.265		0.330
P1 → Performance	0.607				
P2 → Performance	0.821	0.145	10.212	***	
P3 → Performance	0.728	0.142	9.841	***	
R1 → Regulation	0.782				
R2 → Regulation	0.885	0.295	4.395	***	
Model fits	***X²(df)***	***X²/df***	**GFI**	**AGFI**	**CFI**
Results	62.289(33)	1.888	0.968	0.947	0.958
Recommended	p<0.05	<3	0-1	0-1	0-1
Model fits	**IFI**	**TLI**	**NFI**	**RMSEA**	
Results	0.959	0.943	0.916	0.049	
Recommended	0-1	0-1	0-1	<0.08	

*Note: ns = not significant; *p < .10; **p < .05; ***p < .001*

Table 8. SEM-results and null-hypothesis significance. Source: Own elaboration.

The structural model tested six central hypotheses concerning students' ethical perceptions of artificial intelligence in higher education. The empirical results reveal a nuanced picture of how regulation, perceived transformation, cultural context, gender, and knowledge influence students' views on AI ethics.

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Regarding H1, the hypothesis proposed that students who perceive AI as effective would be more likely to consider it ethically appropriate. However, this relationship was not statistically significant ($\beta = 0.080$, ns). This result suggests that the perceived utility or technical effectiveness of AI in academic contexts does not, by itself, drive ethical reasoning among students. While performance remains an important dimension for evaluating technology, it appears insufficient to shape normative judgments on its acceptability or fairness, at least within the observed sample.

H2 received robust empirical support. A significant positive association ($\beta = 0.202$, $p < 0.001$) was observed between students' support for regulatory mechanisms and their ethical evaluations of AI. This confirms that students who value institutional oversight are also more likely to consider the ethical implications of AI tools. Such findings resonate with current regulatory debates in the European Union, where legal frameworks like the AI Act are designed to promote algorithmic transparency and reduce systemic bias in education (Almeida et al., 2022; Gross, 2023). In this regard, regulation functions not only as a legal tool but also as a symbolic guarantee of ethical responsibility, reinforcing students' trust in technological adoption.

A similarly strong relationship was observed for H3, which posited that the perception of change in academia due to AI influences ethical awareness. The hypothesis was confirmed with high significance ($\beta = 0.346$, $p < 0.001$), indicating that students who foresee a transformational impact of AI on academic life are more likely to consider its ethical consequences. This aligns with findings by Malik et al. (2023), who observed that concerns about academic integrity intensify as universities increasingly adopt AI-powered systems. The perception of disruption appears to catalyse reflection on the normative implications of these technologies.

H4 addressed potential cross-cultural differences, proposing that nationality influences students' ethical perceptions of AI. The hypothesis was confirmed ($\beta = 0.131$, $p < 0.05$), with Spanish students expressing stronger ethical concerns than their Romanian counterparts. This result supports the previous literature highlighting the cultural embeddedness of technological values and the role of national regulatory traditions in shaping ethical frameworks (Marginson & Yang, 2022; Wright, 2024). For instance, the emphasis on individual rights in Western European contexts may foster more pronounced ethical expectations regarding AI in education.

Conversely, H5 - which examined the role of gender - was not supported ($\beta = 0.004$, ns). Although previous studies have shown that women may demonstrate higher ethical sensitivity in relation to AI applications, particularly concerning gender bias in algorithms (Abdollahi et al., 2024; Cernadas & Calvo-Iglesias, 2020), such differences were not statistically meaningful in our sample. This could be attributed to the growing generalisation of ethical discourse among youth, transcending traditional gendered moral frameworks.

Finally, H6 hypothesised that greater knowledge of AI would be associated with stronger ethical concern. This was also not supported ($\beta = -0.013$, ns). Despite existing research suggesting that technical understanding enhances awareness of algorithmic risks and fairness (Rasul et al., 2023), our findings suggest that students' ethical positions may be more influenced by external cues - such as regulation or perceived impact - than by their own cognitive mastery of AI systems.

5. Discussion and contributions to the academic debate

AI expands the horizon of scholars, professionals and academics, especially in higher education. The perspective of how each educational context is culturally driven is also reflected in AI management and use. Regarding higher education, these global decentralized systems are a double-edged sword, either promoting diversity and different societies or transferring rancid stereotypes applied to culture, gender, age, nationality, among other factors. These reflections on education are also translated into how AI generates knowledge. Therefore, this paper provides important insights into the relationship between the perception of AI regulation and its ethical judgement in higher education.

Cultures in societies represent a real challenge for this innovative digital world that education is experiencing. This rapid evolution of technology and how it should be applied to higher education lessons and research develop a double task. On the one hand, scholars and academics need to deepen their understanding in AI, and on the other, students are required to participate responsibly in AI implementation. Higher education and, in general, all sectors are completely linked to follow the same direction when talking about AI. For that reason, regulations and the legal framework controlling AI should align with every single one of the areas of the society. Not only should culture be mentioned as the main factor to approach ethics, but also how ethics can determine respect when adopting diverse cultures. Regulations in AI should foster coeducation, diversity, and multiculturalism for the sake of addressing cultural differences and ethical integration. The evidence in this paper shows that AI regulation is perceived as a fundamental factor in ensuring the ethical adoption of this technology, a finding with direct implications for the development of educational policies and regulations in the field of artificial intelligence (ÓhÉigeartaigh et al., 2020; Daly et al., 2019).

The fact that AI Performance is not a significant factor for students' reasoning on AI protocols suggests that is not enough to ensure a responsible and ethical use of it. This is especially relevant in a context where the implementation of AI in education is becoming increasingly common. Therefore, there is a need to look for other cues that support students' reflections and critical thinking that contribute to the improvement of these ethical regulations (Benouachane, 2024; Al Naqbi et al., 2024). Apart from this consideration, it has been emphasised that regulating AI ethics promotes students' trust in this technological implementation. As well, the normative helps academic integrity to be even more safeguarded.

The significant differences found between nationalities reinforce the importance of considering cultural factors when designing and implementing regulatory frameworks for AI in higher education. The fact that Spanish students show greater sensitivity towards ethical aspects compared to Romanian students indicates that perceptions of AI and its ethical use are not homogeneous and are influenced by cultural context. However, gender does not affect this sensitivity as generations have changed and evolved to address the same discourse regarding ethics and morality in this AI panorama.

Independently of cultures, human sight and control should prevail over the automatized digital processes. AI improves academic efficiency, but it is based on data or even creation, and this knowledge generation needs constant revision. Could it be mentioned that this AI also requires maturing more to adjust and be adapted to the needs of the user, a concern which is echoed by Bhimavarapu (2023), who highlights the risk of reduced creative autonomy in writing-based disciplines. In this case, as it has been studied, AI should embrace human diversity, addressing cultures and values. Obviously, experts on this matter have a crucial role in developing intelligence abilities to perceive attitudes and react to these inherent social-cultural behaviours. If such perfection in the performance of AI is achieved, it also means that society has also evolved in terms of values and morality. What is more, students currently work on this ethical outlook in higher education by promoting internationalized contexts where diversity, culture and inclusion are mingled to form a globalized background. Therefore, it is essential to transfer this knowledge and ethical practices to digital automatized scenarios. It has been even confirmed that knowledge of AI does not influence concerns on the ethics, thus it should be mandatory to work on these values and critical judgments on a non-automated basis, but on the traditional educational context of the class scenario.

All in all, the AI panorama encompasses a whole spectrum of areas to improve, and, thus, this paper focuses on the ethic and regulatory one. Policymakers should take into account the emotional and social interpretation that AI lacks to develop a robust legal framework that achieves the aim of decision-making processes, data management and non-detrimental impact on people. Governments ought to tackle this regulatory procedure as AI emotional and social development could help many areas that would experience more personalized and human understanding. For instance, in higher education, learning could become more autonomous, individualized and dynamic.

6. Conclusions and practical implications

The validated SEM model in this study reinforces the need to implement clear and effective regulatory frameworks that guide the use of AI in higher education. Educational institutions and policymakers should consider these cultural differences and student expectations when establishing guidelines that promote the ethical and responsible use of AI. Our findings contribute to the academic debate on AI adoption, providing empirical evidence of the importance of regulation and ethical perceptions in integrating this technology into educational settings.

Students should be prepared for a still non-existing future based on AI, and they should be able to judge ethics on AI tasks. Therefore, future professionals need a regulatory basis on this matter. Data analysis and more detailed practices will be part of the procedures that they will have to confront in their workplaces. It exists a long path between the present AI and the one that is yet to come. However, this favourable process, although arduous, will have a real and meaningful impact on higher education. Without a shadow of a doubt, from the beginning should it be essential to work on ethics and multiculturalism when developing AI procedures and protocols to ensure a smooth transition into the inclusion of this knowledge of engineering within all areas of education.

In higher education, academics and professionals are expected to engage in continuous learning to keep up with digital developments such as artificial intelligence. Addressing the challenges related to AI ethics and regulation will require cooperation between different academic fields and institutions. Without appropriate training, some universities may face difficulties in adapting to these changes, especially in terms of digital and international integration. Basic intercultural skills and international collaboration may help inform regulatory discussions. Sharing knowledge between researchers, educators, and policymakers can contribute to the development of frameworks that aim to be inclusive and balanced.

Being all previous aspects of AI considered, it can be said that ethics and culture in terms of regulatory aspects should be stated in order to promote justice and fairness among data, avoid biased contexts and respect cultural diversity. In other words, contributing to the responsibility, transparency and accountability of the social impact that AI may have on diverse social lifestyles.

7. Limitations of the study

The previous research presents certain limitations that may have restricted the depth of the comparison between participants of the two nationalities. Specifically, the sample could have been broadened by including university professors or staff members from the institutions where the data were collected. This expansion would have allowed for a more comprehensive analysis of some of the proposed hypotheses. For instance, the level of cognitive mastery typically exhibited by these academic profiles could provide additional insights into how such expertise influences their perceptions and concerns regarding the ethical implications of AI.

8. Future lines of research

This paper determines the factors that need to be considered when developing the regulatory framework of AI in higher education. Ethics and cultures should be present within this automatized digital era if the society wants to evolve within the AI panorama. Therefore, future field of research is opened to inquire how ethics and cultures have been considered and put into practice within further regulatory backgrounds and whether the higher education experts and students have controlled, and above all, have managed these biased data in vulnerable areas of AI application.

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