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ORIGINAL ARTICLE

Explaining higher education social sciences students' misuse of generative artificial intelligence: evidence from a multidimensional ethics scale

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Abstract

The growing presence of generative artificial intelligence (GenAI), such as ChatGPT, in higher education raises significant ethical concerns, particularly regarding its misuse in academic essay writing. This study examines how university students enrolled in social science programs at two Spanish universities ethically evaluate a typical misuse of GenAI—namely, producing academic essays with minimal human editing. Drawing on the Multidimensional Ethics Scale (MES), four ethical dimensions—moral equity, relativism, consequentialism, and deontology—together with gender and employment status, are analyzed using a dual-method approach combining partial least squares structural equation modeling (PLS-SEM) and fuzzy-set qualitative comparative analysis (fsQCA). The PLS-SEM results show that only consequentialism and relativism significantly influence students' intention to use GenAI, indicating a predominant reliance on perceived utility and contextual social norms. In contrast, moral equity and deontology do not exhibit statistically significant effects. Complementing these findings, the fsQCA identifies multiple, asymmetric causal configurations leading to both acceptance and rejection of GenAI misuse, underscoring that adoption and non-adoption are driven by distinct underlying mechanisms. By integrating correlational and configurational perspectives, this study advances understanding of the ethical complexity surrounding GenAI use in higher education. The findings highlight the need for differentiated educational strategies that account for heterogeneous student profiles and diverse moral reasoning frameworks.

Keywords Generative artificial intelligence · Academic ethics · Essay writing · Multidimensional ethics scale · PLS-SEM · FsQCA

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Introduction

In recent years, artificial intelligence (AI)-based tools have experienced remarkable and rapid progress, positioning themselves as key technologies across multiple spheres of everyday life (Dwivedi et al. 2023). Within higher education, the impact of AI has been particularly notable. Generative artificial intelligence (GenAI), such as ChatGPT, has opened new possibilities in teaching and learning processes (Prajapaty et al., 2024). These technologies enable a wide range of applications, from automating routine tasks to personalizing learning experiences, offering immediate answers to complex questions, assisting with academic writing, generating summaries, and even providing specialized virtual tutoring (Mandal et al. 2025).

Despite the considerable potential benefits of GenAI, such as augmenting human capabilities, fostering innovation, and addressing global challenges, significant concerns persist regarding privacy, security, unemployment, and the potential widening of social inequalities (Acampa 2025). In educational contexts, the use of GenAI raises additional concerns related to ethics, equity, and academic integrity (Batista et al. 2024). Unregulated or inappropriate use may produce counterproductive effects, including discouraging the development of basic skills such as written expression (Alier et al. 2024) and hindering higher-order cognitive abilities like critical thinking, logical reasoning, and creativity (Farangi et al. 2025). When GenAI substitutes for active learning processes, it risks fostering passive engagement with knowledge rather than encouraging autonomous and reflective learning (Licht 2024).

One of the most widely used forms of assessment in higher education is the academic essay, typically submitted by a predetermined deadline. Essays play a central role in evaluating student learning, particularly in the social sciences, as they foster a wide range of cognitive competencies. This assessment format is especially effective in developing analytical thinking, creativity, and personal reflection. These skills are essential in both academic and professional contexts (Dahl et al. 2023). Essays require students to synthesize information, construct coherent arguments, and demonstrate understanding through structured writing. Prior research consistently shows that sustained engagement with essay writing enhances students' critical thinking abilities, as it demands the analysis, evaluation, and articulation of complex ideas (Ashley et al., 2017).

In this context, the intensive misuse of GenAI for writing academic essays may fundamentally undermine the pedagogical objectives of this assessment method (Aylsworth and Castro 2024). Unlike traditional plagiarism, which involves both appropriation and deception by presenting another person's work as one's own, the improper use of GenAI may rely primarily on deception, without directly copying external content (Shaw 2025). This distinction may lead students to perceive GenAI misuse as less morally problematic, even though it clearly constitutes academic dishonesty. Moreover, GenAI-generated text is often original and does not appear in existing databases, making it substantially more difficult to detect using conventional plagiarism detection tools (Farrelly and Baker 2023).

The central role of essays in higher education assessment, combined with the particular risks associated with extensive GenAI use in this format, motivates the present study. Specifically, the study examines the following scenario: a student must submit an academic essay by a fixed deadline. As the deadline approaches, the student realizes that they are unable to produce a satisfactory piece of work. As an alternative, the student considers submitting an essay that has been largely generated by GenAI, with only minimal human editing. The student must then evaluate the ethical appropriateness of this course of action.

This study analyzes students' ethical evaluations of GenAI use from an interpretive perspective, recognizing that students construct their own criteria for legitimate conduct through observation and the implicit messages conveyed by peers and their broader academic environment (Thornberg 2007). These interpretive frameworks are shaped through informal learning dynamics, where social norms and interpersonal interactions—whether explicit or implicit—play a decisive role in influencing academic behavior (Grühn and Cheng 2014).

Labeling a given behavior as simply "ethical" or "unethical" is overly reductive. In the proposed scenario, students are likely to consider multiple factors, including perceived fairness, compliance with institutional norms, and performance-related pressures (Rua et al. 2024). Accordingly, ethical judgment cannot be reduced to a single moral criterion; rather, individuals draw on arguments derived from different moral philosophy traditions, such as moral equity, consequentialism, and deontology (Pérez-Portabella et al. 2025). In line with this reasoning, the present study adopts an adaptation of the Multidimensional Ethics Scale (MES) (Reidenbach and Robin 1990), which captures ethical evaluations grounded in diverse moral theories.

The MES has been widely applied to ethical decision-making across multiple domains, including business and commerce (Jones and Leonard 2016; Nguyen et al. 2008), relationships between salespeople and organizations (Santalla-Banderali et al. 2024), consumer decision-making (Shawver and Sennetti 2009), and the acceptance of controversial technologies such as implantable devices (Ahadzadeh et al. 2023; Pelegrín-Borondo et al. 2020). It has also been employed in academic contexts to analyze ethically sensitive behaviors. These include individual-level decisions, such as essay plagiarism (Jung 2009; Leonard et al. 2017; Prashar et al. 2024; Yang 2012), falsification of academic documents (Yang 2012), piracy (Jung 2009), and privacy violations involving peers (Jung 2009), as well as collective behaviors, such as unauthorized collaborative communication during examinations (Leonard et al. 2017).

The analytical framework adopted in this study is presented in Fig. 1. The framework integrates two complementary perspectives: a correlational approach and a configurational approach. Students' intention to use GenAI in the proposed scenario is explained by four ethical dimensions—moral equity, moral relativism, consequentialism, and deontology—as well as two sociodemographic variables (gender and employment status). Based on this framework, the study addresses the following research questions:

RQ1: What is the overall impact of each ethical dimension and students' personal circumstances on the decision to make intensive use of GenAI to write an academic essay?

To address RQ1, a partial least squares structural equation modeling (PLS-SEM) approach is employed, corresponding to the correlational framework depicted in Fig. 1. Additionally, a preliminary analysis of descriptive statistics provides an

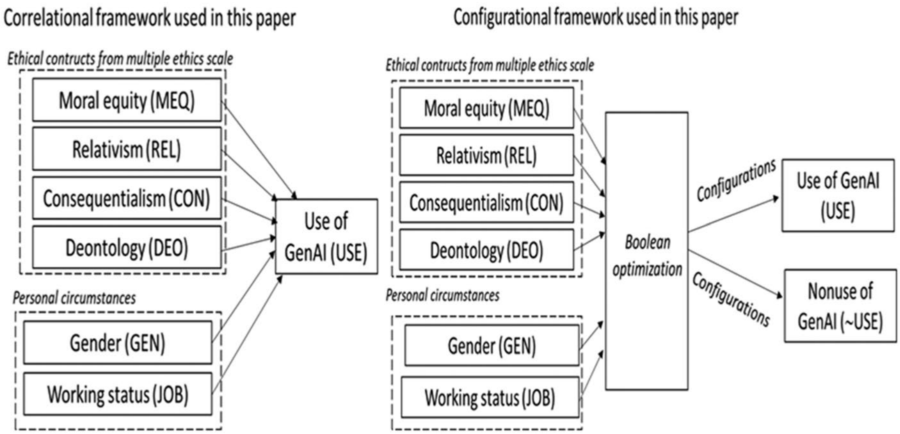

Fig. 1 Correlational and configurational frameworks used in this study

initial overview of participants' prevailing attitudes toward the constructs under investigation.

RQ2: How do ethical variables and students' personal circumstances combine to result in either the use or non-use of GenAI for essay writing?

In complex phenomena such as technology adoption, outcomes often emerge from multiple causal pathways reflecting diverse user profiles and motivations (Arias-Oliva et al. 2024). Moreover, such phenomena are typically asymmetric: the factors leading to adoption are not simply the inverse of those leading to rejection. In the context of technology acceptance, while perceived unacceptability may lead to rejection, perceived acceptability does not necessarily result in adoption (Gauttier 2019). Under these conditions, fuzzy-set qualitative comparative analysis (fsQCA) is particularly well suited, as it enables the identification of different configurations of conditions that jointly produce a given outcome (Woodside 2014).

Although fsQCA is less frequently used than correlational techniques such as PLS-SEM in technology acceptance research, it has been shown to provide substantial added value by identifying heterogeneous profiles associated with adoption outcomes (Arias-Oliva et al. 2024). By combining PLS-SEM and fsQCA, the present study captures both the net effects of ethical variables and the complex configurations through which ethical judgments and personal circumstances shape students' use of GenAI.

Model development

Statistical hypotheses regarding the influence of ethical constructs on GenAI use

Moral equity

Moral equity (MEQ) encompasses a person's judgment regarding fairness, justice, and broader notions of right and wrong (Leonard et al. 2017). The concept of morality implies an impartial obligation to promote fairness, acknowledge the breadth of moral principles—including equality and rights—and question inequality and injustice (Killen 2018). From the capabilities approach, justice should not be measured solely by available resources or formal liberties, but by what people are actually able to do and become (Nussbaum and Sen 1993).

Under exceptional circumstances, using GenAI to write an essay may be seen as a tool to level the playing field, especially when students face significant barriers to meeting deadlines—such as the need to balance studies with paid employment, which is often the main reason cited by working students (Soelistiyono and Chen 2023). Student decisions in high-pressure contexts, with limited resources or time constraints, are not always motivated by a desire to cheat but rather by a perception of structural injustice and a need to "even the odds" (Rosen and Dreskin 2024).

Moreover, while GenAI use may be perceived as unfair, one could argue that if access is free or more affordable than other dishonest alternatives (such as paying someone to write an essay), the method—although unethical—remains egalitarian. This is the case with free and user-friendly GenAI tools like DeepSeek or ChatGPT 3.5 (Dwivedi et al. 2023).

Of course, many arguments against this practice from MEQ perspective exist. The use of such technologies may undermine the value of meaningful effort (Kasneci et al. 2023), which completely distorts the intended goals of essay writing. Justice is not only related to outcomes but also to individual processes and personal commitment to learning (Dalbert et al. 2007). If a student uses GenAI as a substitute for their own work, the moral principle of authenticity is weakened, and the intended development of writing skills and critical thinking—which the university aims to foster—is undermined (Licht 2024; Dahl et al. 2023). Furthermore, students have a moral duty to respect and cultivate their autonomy, understood as the human capacity to reflect, make decisions, and pursue personal goals. Writing one's own essays is a way of exercising that autonomy. Using GenAI for this task means giving up a valuable opportunity for rational and moral self-development (Aylsworth and Castro 2024).

Misuse of GenAI also likely generates unfair competition. When some students engage in academically dishonest practices to boost their performance, it creates clear inequity for those who choose not to do so (Burgason et al. 2019). In this way, GenAI use in this scenario introduces an unfair advantage in evaluative contexts (Oates and Johnson 2025), violating the Rawlsian principle that inequalities are only justifiable if they benefit the least advantaged.

Hypothesis 1 (H1): *A positive perception of GenAI use from the standpoint of moral equity is positively related to the intention to use it to write an essay.*

Relativism

Relativism (REL) is a philosophical position asserting that moral and ethical judgments are neither absolute nor universal, but rather contingent upon cultural, historical, social, or individual contexts. From this perspective, what is considered "right" or "wrong" varies across situations, and no single objective standard governs moral evaluation (Baghramian and Carter 2025).

Within a relativist framework, the use of GenAI as a study aid may be deemed morally acceptable depending on the intended purpose (Reimer 2024). However, its intensive use in producing academic essays is generally perceived more negatively (Shaw 2025). Peer attitudes toward academic practices exert a strong influence on students' behavior, shaping decisions through both explicit and implicit social cues (Andersen and Hjortskov 2019). Consequently, the influence of peers (Strzelecki 2024) and educators (Tlais et al. 2025) plays a decisive role in students' engagement with GenAI, irrespective of its specific use.

Students may perceive a "peer cheating effect", which is among the strongest predictors of individual academic misconduct. Observing peers engage in dishonest practices increases the likelihood of imitation, as students rely on social comparison to regulate their own behavior (Perry et al. 2025). This dynamic contributes to the normalization of misconduct through moral neutralization strategies—such as "everyone does it"—that allow students to reduce cognitive dissonance without fully abandoning their ethical standards (Zhao et al. 2022). Normative ambiguity further exacerbates this issue, as many students lack clarity regarding which practices constitute academic dishonesty (Burrus et al. 2007), potentially facilitating questionable GenAI use.

The academic environment plays a central role in either discouraging or enabling misconduct by shaping shared norms and individual perceptions of acceptable behavior. Clear institutional policies, strong academic leadership, and faculty coordination are associated with lower levels of academic dishonesty, as they foster transparent and ethical learning environments (Ramberg and Modin 2019). Nevertheless, moral disengagement remains a powerful predictor of academic misconduct, underscoring the importance of addressing internal cognitive justifications alongside formal regulations (Perry et al., 2025).

From the perspective of technology acceptance models like TAM and UTAUT, social influence has been identified as a key factor in understanding technology adoption—including GenAI. This holds true in educational contexts, both from the perspectives of students (Amin et al. 2025; Elshaer et al. 2024; Sobaih et al. 2024) and educators and researchers (Strzelecki et al. 2024).

Hypothesis 2 (H2): *A positive perception of GenAI use from the standpoint of relativism is positively related to the intention to use it to write an essay.*

Consequentialism

Consequentialism (CON) holds that an action is morally permissible if the overall utility of performing it is, on balance, positive (Sinnott-Armstrong 2023). This utility may be framed from either egoistic or utilitarian perspectives. Egoism suggests that an action is morally acceptable if it promotes personal benefit, whether long-term or driven by short-term hedonistic goals (Deigh 2010). Utilitarianism, on the other hand, deems an action acceptable if it positively impacts society (Rae 2018).

From an egoistic standpoint, using GenAI may be justified as it enables quick and organized access to information (Menon and Shilpa 2023), freeing up personal resources that can be allocated to other academic activities the student perceives as more valuable or to address the issues that prevented them from dedicating sufficient time to essay writing. In this sense, reconciling personal circumstances with academic demands increases individual well-being, aligning with the hedonistic principles of moral egoism (Shaver 2023).

However, GenAI use may also be counterproductive from an egoistic standpoint if it undermines learning outcomes or academic performance (Aylsworth and Castro 2024). GenAI-generated content may contain inaccuracies, biases, or hallucinations, potentially resulting in lower-quality submissions and poorer evaluations (Oates and Johnson 2025).

Reputation constitutes an important component of self-interest (Tomova et al. 2021). In institutions where GenAI use is restricted or discouraged (Licht 2024), public exposure of such practices may lead to reputational damage and loss of trust. Accordingly, feelings of guilt and ethical discomfort have been shown to reduce the perceived usefulness of GenAI in morally sensitive contexts (Jo 2026).

In the long term, excessive reliance on GenAI may hinder skill development and compromise students' educational trajectories (Yu 2023), ultimately affecting professional preparedness and employability (Licht 2024). At a collective level, widespread misuse of GenAI may erode linguistic diversity, human creativity, and knowledge quality (Acampa 2025), while diminishing engagement with academic texts and weakening higher education outcomes (Monib et al. 2025).

From a utilitarian perspective, a particularly salient concern relates to the potential erosion of institutional legitimacy. Extensive GenAI misuse in academic assessment may undermine the credibility of higher education institutions, raising doubts about the validity of degrees and the fairness of evaluation processes (Kasneci et al. 2023). This concern is exacerbated by the limited reliability of GenAI detection tools, which exhibit both false negatives and false positives (Farrelly and Baker 2023; Kasneci et al. 2023).

Perceived usefulness and efficiency, that are closely tied to achieving personal and social goals, have been identified as key drivers in the adoption of AI-based technologies, including GenAI (Camilleri 2024; Ibrahim et al. 2025). This finding is consistent across educational contexts (Al Darayseh 2023; Al-Okaily 2025; Panggabean and Silalahi 2025; Sobaih et al. 2024; Strzelecki 2024). Moreover, the importance of hedonistic goals in academic GenAI usage (Strzelecki et al. 2024) reinforces the potential relevance of consequentialism in explaining GenAI adoption.

Hypothesis 3 (H3): *A positive perception of GenAI use from the standpoint of consequentialism is positively related to the intention to use it to write an essay.*

Deontology

Deontology (DEO), particularly in its contractualist form, asserts that moral judgments should be grounded in adherence to norms derived from collectively accepted principles, rather than solely on outcomes (Alexander and Moore 2024). According to this perspective, individuals act under the perception of an implicit contract with society, which establishes mutual obligations (Reidenbach and Robin 1990). These moral duties bind individuals regardless of the consequences (Alexander and Moore

2024). Within educational settings, this perspective emphasizes students' responsibilities as members of academic communities and future professionals (De Ruyter and Schinkel 2017).

Students' implicit contracts with universities and society include commitments to honest conduct and meaningful learning (Ramberg and Modin 2019). From this viewpoint, intensive GenAI use in essay writing violates established academic norms. Students are influenced by family expectations, social norms, and institutional standards—factors that shape motivation and performance (Chen 2023; Li et al. 2023). Family guidance plays a central role, as positive reinforcement can enhance student engagement and achievement (Shi et al. 2023), creating a sense of responsibility that encompasses both personal goals and collective duties. This intersection of personal and social expectations can foster strong motivation to fulfill student obligations. Students often view their educational journey as a reflection not only of their own aspirations but also of those of their families and communities (Vasquez-Salgado et al. 2021).

At the same time, students may interpret academic success itself as a moral duty, particularly in publicly funded institutions, where educational attainment represents a form of reciprocity toward society (Barbosa 2024; Ruyter and Schinkel 2017). Tensions may arise, however, when institutional rules conflict with performance pressures or personal constraints (Rua et al. 2024). In such cases, GenAI use may be self-justified as a means of fulfilling perceived obligations to achieve high grades, despite violating learning-oriented norms.

Moreover, unsupervised GenAI use may infringe professional ethics, legal frameworks, or contractual obligations related to copyright and authorship (Rudko & Bashirpour Bonab 2025). Increasingly, universities emphasize holistic education that integrates civic responsibility and social awareness (Berei 2020), which further underscores the ethical relevance of considering the environmental impact of GenAI, given its substantial energy consumption and carbon footprint (Licht 2024).

Deontological reasoning has been shown to influence ethical decision-making in academic contexts involving misconduct (Leonard et al. 2017; Yang 2012).

Hypothesis 4 (H4): *A positive perception of GenAI use from the standpoint of deontology is positively related to the intention to use it to write an essay.*

The influence of gender and employment status on ethical perceptions about employing GenAI

Differences in perceptions of GenAI use by gender

Prior research has consistently documented gender-based differences in ethical perceptions, showing that men and women often approach moral dilemmas in systematically different ways (Nguyen et al. 2008). Such differences have been attributed to a combination of biological, cultural, and situational factors that shape ethical reasoning and intentions (Rachels and Rachels 2012). Empirical evidence suggests that men tend to rely more heavily on utilitarian reasoning when confronted with ethical challenges, whereas women are more likely to adopt deontological perspectives, emphasizing adherence to moral duties rather than the evaluation of outcomes (Pilcher and Smith 2024).

These divergent tendencies are often explained through gender socialization theory, which posits that individuals internalize distinct value systems and moral priorities from early childhood based on gendered social expectations. As a result, differences in ethical judgment arise not from disparities in cognitive ability, but from socially constructed moral orientations shaped through lifelong socialization processes (Roxas and Stoneback 2004).

Across diverse cultural contexts, women have been found to display more altruistic behavior, even when such behavior entails personal sacrifice, which may align more closely with principles of moral equity. In contrast, men are more likely to exhibit behaviors oriented toward self-affirmation or instrumental goal achievement (Peng 2022). Overall, empirical studies indicate that women tend to express stricter ethical judgments than men (Nguyen et al. 2008). This pattern has also been observed in research on GenAI use in higher education, where women report lower confidence in managing academic integrity issues related to these technologies (Bikanga Ada 2024).

Hypothesis 5 (H5): *Being male is positively associated with the intention to use GenAI.*

The student's employment status

Combining stable employment with university studies is now widespread globally, driven by economic, academic, and personal reasons (Standley and Fesmer 2023). Roughly one in three students in Spain maintain ongoing employment alongside their academic studies (Simón et al. 2017). The reasons behind this dual activity vary based on socioeconomic context, work hours, kind of occupation and the student's personal motivations (Simón et al. 2017).

Balancing demanding academic requirements with significant employment commitments frequently produces elevated levels of stress and exhaustion, which can negatively impact academic achievement (Chantrea et al. 2023; Soelistiyono and Chen 2023). Empirical research indicates that exceeding approximately 20 working hours per week is often associated with poorer academic outcomes and, in extreme cases, an increased risk of dropout (Pacífico and Gandolfo 2016).

Several studies have documented a tension between students' employment and academic roles, whereby intensive academic engagement may interfere with job performance and vice versa (Wyland et al. 2013). The extent to which employment affects academic success depends largely on which role the student perceives as their primary obligation (Brosnan et al. 2023).

Given their distinct responsibilities, time constraints, and social contexts, working students may develop different ethical evaluations regarding the acceptable use of GenAI. Because they are more likely to experience conflicts between academic demands and other life domains, working students may be more inclined to consider intensive GenAI use as a means of coping with competing obligations.

Hypothesis 6 (H6): *Having greater work obligations is positively associated with the intention to use GenAI intensively for essay writing.*

Development of configurational propositions

The hypotheses developed in Sect. 2.1 and 2.2 are designed to address RQ1 by examining the net effects of ethical and sociodemographic variables on students' intention to use GenAI. These hypotheses are tested using a correlational approach—specifically, partial least squares structural equation modeling (PLS-SEM)—which estimates a single directional effect for each explanatory variable across the entire sample.

However, correlational methods are inherently variable-oriented and therefore limited in their ability to capture the existence of multiple causal pathways leading to the same outcome. In complex behavioral phenomena such as technology adoption, different combinations of conditions may give rise to similar decisions. Identifying these alternative pathways underlies RQ2.

Fuzzy-set qualitative comparative analysis (fsQCA), a case-oriented method, is particularly well suited to this task, as it allows outcomes to be explained by multiple configurations of conditions rather than by isolated net effects (Woodside 2014). Through the calibration of set memberships and the use of Boolean algebra, fsQCA identifies combinations of causal conditions that are sufficient to produce a given outcome (Ragin 1999).

Moreover, there is no single typology of technology users (Birkland 2019), nor of non-users (Gauttier 2019). Accordingly, fsQCA offers a powerful tool to study the acceptance of new technologies, capturing nuances that correlational analysis cannot (Arias-Oliva et al. 2024; Pappas and Woodside 2021). In our case, it enables the identification of multiple configurations that define potential user and non-user profiles regarding GenAI use in essay writing.

The application of configurational methods to decision-making based on MES has been explored in several studies. For example, Andrés-Sánchez et al. (2021) found that both the acceptance and rejection of cyborg technologies stem from multiple configurations combining positive and negative evaluations across different ethical dimensions. Similar findings were reported by Arias-Oliva et al. (2021) in their analysis of ethical judgments of immunity passports.

Unlike correlational approaches, fsQCA does not test strong, symmetric hypotheses, but instead formulates context-dependent generalizations, often referred to as "soft laws" or configurational propositions (Rutten and Rubinson 2022). In line with this logic, the following propositions are advanced:

Proposition 1 (P1): *Configurations anteceding the intention to use GenAI commonly include an association of the following conditions: positive evaluations of moral equity, relativism, consequentialism, and deontology; being male; and having work obligations.*

At the same time, pathways leading to technology rejection are not uniform, but vary according to individuals' cognitive, material, and emotional circumstances. A widely accepted taxonomy distinguishes between resisters, rejecters, expelled users, and excluded users (Gauttier 2019). Accordingly, the following proposition is formulated:

Proposition 2 (P2): *Configurations anteceding to the no intention to use GenAI commonly include an association of the following conditions: negative evaluations of moral equity*, *relativism*, *consequentialism*, *and deontology; being female; and having no work obligations.*

Importantly, user and non-user profiles are not mirror images of one another. While some individuals may reject GenAI due to concerns related to moral equity or deontology, those who view GenAI as morally acceptable do not necessarily choose to use it unless they also perceive clear benefits from a utilitarian or relativist perspective. In other words, lack of acceptability may lead to rejection, but acceptability does not guarantee adoption (Gauttier 2019). Moreover, user typologies such as enthusiasts or practicalists (Birkland 2019) do not correspond directly to non-user categories. This asymmetry leads to the third proposition:

Proposition 3 (P3): *The configurational explanations of GenAI use and non-use are asymmetric.*

Data and methods

Sampling

The present study was conducted with students from two Spanish universities enrolled in social science programs, specifically degrees such as Business Administration, Economics, and Social Work. These disciplines are characterized by a strong emphasis on communicative competencies—both oral and written—as well as on understanding the humanistic dimensions of behavior. Within the social sciences, the academic essay is a widely used method of instruction and assessment in higher education (Lukeman 1992).

The sample was obtained through purposive sampling, and data collection took place during the spring of 2025. Data were gathered using an anonymous, voluntary, and self-administered online questionnaire. The anonymity and voluntary nature of participation were intended to encourage candid responses, thereby reducing social desirability bias and fostering more reflective ethical evaluations.

Sample profile and sample size

The survey was distributed via a digital link that restricted responses to one per IP address, thereby ensuring the uniqueness of each participation.

The total number of valid responses was 151. Table 1 summarizes the demographic and academic characteristics of the sample, including gender, age, perceived academic performance, and employment status. Into regard to the relatively modest size of the sample, it should be noted that recruiting participants for studies in which

Table 1 Sample profile and descriptive characteristics of respondents

Variable	Respondents
Sex	
Man	53 (35%)
Woman	98 (65%)
Age	
<=20 years	50 (33%)
21 years	33 (22%)
22 years	27 (18%)
>=23 years	40 (26%)
Nonanswered	1 (1%)
Perceived academic performance	
Average or lower	107 (71%)
Higher than average	44 (29%)
Working status	
Full-time employment	58 (38%)
Part-time, or no work	93 (63%)

individuals, even anonymously, acknowledge the possibility of engaging in ethically questionable behaviors is challenging. Thus, in research applying the MES, modest sample sizes are common. For instance, with samples smaller than or comparable to ours, prior studies range from 67 observations (Cruz et al. 2000) to 179 in the first study by Rua et al. (2024). Similarly, Leonard et al. (2017) relied on 90 observations, Rua et al. (2024) on 87 in their second study, Jung (2009) on 101, Shawver and Sennetti (2007) on 120 students, and Cohen et al. (2001) on 123. However, we consider the sample size to be adequate for the quantitative analyses involved in this study, which include the use of PLS-SEM (to address RQ1) and fsQCA (for RQ2).

Regarding PLS-SEM, as illustrated in Fig. 1, the model includes six predictor variables. According to the "ten times rule" (Hair et al. 2019), the minimum required sample size would be 60 cases, given the six regressors. Applying a more conservative version of this rule—"twenty times the number of predictors" (Schumacker and Lomax 2010)—raises the threshold to 120 cases. Additionally, a power analysis conducted using G*Power 3.1.0 (Faul et al. 2009) confirmed that with a sample of 151 participants, it is possible to detect a minimum model effect size of 0.1 (equivalent to an R^2 of 9.09%, considered small) with 80% statistical power at a 5% significance level. When statistical power is applied to test the significance of path coefficients, a significance level of 5% allows for 80% power to detect effect sizes of approximately $f^2 = 0.06$ (close to small).

As for fsQCA, it does not require a particularly large minimum sample size; however, authors such as Fiss (2011) suggest a threshold of around 30–50 cases. Thus, in this second case as well, the sample size can be considered adequate.

Measurement model

The questionnaire began by introducing the scenario to be evaluated by the respondents:

"*Imagine the following situation: the essay submission deadline is approaching, and you have not had enough time to write it. You decide to ask an artificial intel-*

ligence tool, such as ChatGPT, to generate most of the content—introduction, body, and conclusion—and then make only minor edits before submitting it as your own.

Based on this scenario, reflect on the use of generative artificial intelligence in the academic context."

Prior to data collection, the questionnaire, written in Spanish, was reviewed by four faculty members and two students. Their feedback contributed to improving the clarity and readability of the instrument, without altering its substantive content.

Table 2 displays the questions employed to capture the ethical judgments developed in Sect. 2.1. They are grounded on the MES proposed by Shawver and Sennetti (2009). Respondents rated each item from 0 to 10 (an eleven point Likert scale), indicating their level of agreement with the statements, ranging from "strongly disagree" to "strongly agree." This response format has been employed in multiple MES-based studies, including research on cyborg technologies (Pelegrín-Borondo et al. 2020; Reinares-Lara et al. 2018), immunity passports (Arias-Oliva et al. 2021), and emerging sports technologies (de Andrés-Sánchez and de Torres-Burgos 2021).

Gender was operationalized as a binary variable (female and male). Employment status was captured using three categories: students with full-time employment, those with part-time or temporary employment, and those with no employment obligations.

Table 2 Descriptive statistics of measurement items and assessment of scale reliability and validity

Item	Mean	Standard Deviation	Factor loading
USE (CA=NA, CR=NA, AVE=1)			
USE: I will use Gen AI in this scenario	5.285	2.899	1
Moral equity (MEQ) (CA=0.69, CR=0.86, AVE=0.76)			
MEQ1: Using GenAI in this scenario is fair.	6.735	2.686	0.853
MEQ2: Using GenAI in this scenario is equitable.	4.808	2.909	0.894
Relativism (REL) (CA=0.88, CR=0.93, AVE=0.81)			
REL1: Using GenAI in this scenario is accepted by my peers.	6.119	2.852	0.908
REL2: Using GenAI in this scenario is accepted by people in my environment.	5.629	2.879	0.96
REL3: Using GenAI in this scenario is acceptable to people whose opinions I respect.	4.298	3.07	0.825
Consequentialism (CON) (CA=0.91, CR=0.94, AVE=0.79)			
CON1: Using GenAI in this scenario will bring relevance and prestige.	6.808	2.706	0.876
CON2: Using GenAI in this scenario is rewarding.	4.96	3.168	0.849
CON3: Using GenAI in this scenario is useful.	6.808	2.79	0.921
CON4: Using GenAI in this scenario has a good cost–benefit balance.	5.987	2.87	0.906
Deontology (DEO) (CA=0.94, CR=0.97, AVE=0.95)			
DEO1: Using GenAI in this scenario adheres to an implicit social contract.	4.523	3.094	0.972
DEO2: Using GenAI in this scenario conforms to the expectations placed upon me as a student.	4.311	3.15	0.974
GEN=Dummy variable (baseline, men)			1
JOB=Variable with three levels (0=No employment; 0.5=Part-time or temporary employment and 1=Full-time stable employment)			1

Note: (a) NA=Does not apply (b) CA=Cronbach's alpha; CR=composite reliability; AVE=average variance extracted. (c) Factor loadings correspond to standardized estimates. All items were measured using an 11-point Likert scale ranging from 0 (strongly disagree) to 10 (strongly agree)

The outcome variable—students' intention to use GenAI to produce the essay—was measured using a single item rated on the same 11-point Likert scale.

Data analysis

The analytical strategy followed a sequential approach designed to address RQ1 and RQ2 in turn. First, the measurement model was assessed by examining internal consistency, convergent validity, and discriminant validity, after which factor scores were computed. This preliminary step is common to both PLS-SEM and fsQCA analyses (Hair et al. 2019; Pappas and Woodside 2021).

For the dependent variable (USE), standardized scores on the 11-point scale were employed. Ethical constructs were represented using standardized factor scores derived from the measurement model. Gender (GEN) was modeled as a dummy variable, with 0 representing male and 1 representing female. Employment status (JOB) was calibrated to reflect work intensity: 1 for full-time employment, 0.5 for part-time or temporary employment, and 0 for no employment.

Second, the structural model was estimated using PLS-SEM, as depicted in Fig. 1. This step addressed RQ1 by assessing the significance of the hypothesized relationships, overall model fit, and explanatory power. The procedure followed established guidelines (Hair et al. 2019), and predictive performance was evaluated using the cross-validated predictive ability test (CVPAT) (Sharma et al. 2023).

To address RQ2, a separate fsQCA was conducted for both USE and its negation (~USE), following the procedure outlined by Pappas and Woodside (2021). For USE and the ethical constructs, membership functions were calibrated using standardized factor scores. Thresholds for full non-membership, the crossover point, and full membership were set at the 15th, 50th, and 85th percentiles, respectively, with linear interpolation applied between these points. For GEN and JOB, the same calibration values used in the PLS-SEM model were retained. Negated conditions (~X) were computed as the complement of the corresponding membership scores.

Following calibration, necessity analyses were conducted for all conditions and their negations with respect to USE and ~USE. Subsequently, sufficient conditions were identified by deriving intermediate and parsimonious solutions. The intermediate solutions were informed by the correlational hypotheses (H1–H6). Conditions appearing in both intermediate and parsimonious solutions were classified as core, whereas those appearing only in intermediate solutions were classified as peripheral (Fiss 2011).

Consistency values were used to assess the empirical relevance of each configuration (with values above 0.80 considered acceptable), while coverage values indicated the proportion of cases explained by each solution (Pappas and Woodside 2021). The resulting fsQCA solutions for USE provided empirical support for Proposition 1, those for ~USE informed Proposition 2, and their comparison served to evaluate Proposition 3.

El análisis PLS-SEM fue realizado con SmartPLS 4.1.1.1.6 (Ringle et al. 2024) and fsQCA with (Ragin and Davey 2022).

Results

Descriptive statistics and analysis of the measurement model

Table 2 reports the means and standard deviations of the measurement items, excluding sociodemographic variables. Although the scenario evaluated may clearly be interpreted as a case of academic dishonesty, several items—MEQ2, REL3, CON2, DEO1, and DEO2—display mean values below the midpoint of the scale, suggesting ambivalent or critical ethical evaluations among respondents.

Regarding scale reliability and validity, the measurement model exhibits satisfactory psychometric properties. As shown in Table 2, Cronbach's alpha and composite reliability values exceed the recommended threshold of 0.70 for all constructs, with the exception of moral equity, whose Cronbach's alpha reaches 0.69. Given that this construct meets all other reliability and validity criteria (including factor loadings above 0.70, composite reliability above 0.70, and an average variance extracted (AVE) exceeding 0.50) it is considered to demonstrate acceptable internal consistency.

Convergent validity is further supported by standardized factor loadings exceeding the 0.70 benchmark and AVE values above 0.50 for all constructs. Discriminant validity is also confirmed, as shown in Table 3: the square roots of the AVE values are greater than the corresponding inter-construct correlations, and none of these correlations exceeds the threshold of 0.85 (Cheung et al. 2024).

PLS-SEM assessment. Response to the research question 1

Table 4 presents the results of the structural model developed in Sect. 2.1–2.2. Regarding model fit quality, the coefficient of determination (R^2) is 62.8%, suggesting a moderate to substantial level of explanatory power (Hair et al. 2019). Additionally, the standardized root mean squared residual (SRMR) does not exceed 0.1, indicating an acceptable model fit. It should be noted that, although the sample size is not particularly large, achieving a statistical power of 80% for assessing the validity of the model required a coefficient of determination of 9%, a value that is substantially exceeded.

Table 3 Pearson's correlation matrix and squared roots of average variance extracted

	USE	MEQ	REL	CON	DEO	GEN	JOB
USE	1						
MEQ	0.665	0.874					
REL	0.712	0.807	0.899				
CON	0.774	0.807	0.786	0.888			
DEO	0.576	0.712	0.737	0.704	0.973		
GEN	0.001	-0.031	0.019	-0.042	-0.109	1	
JOB	0.183	0.151	0.3	0.204	0.303	-0.019	1

Note: The square roots of the average variance extracted (AVE) are reported on the diagonal. Off-diagonal elements represent Pearson correlation coefficients

Table 4 Results of the PLS-SEM structural model explaining students' intention to use GenAI

Relation	β	SD	f^2	VIF	t-ratio	*p* value	Decision
H1: MEQ-> USE	-0.016	0.101	<0.001	3.954	0.158	0.875	Rejection
H2: REL-> USE	0.298	0.122	0.06	3.978	2.449	0.014	Acceptance
H3: CON-> USE	0.581	0.08	0.259	3.504	7.258	<0.001	Acceptance
H4: DEO-> USE	-0.037	0.115	0.001	2.636	0.318	0.751	Rejection
H5: GEN-> USE	0.034	0.122	0.001	1.037	0.276	0.783	Rejection
H6: JOB-> USE	-0.012	0.055	<0.001	1.168	0.213	0.831	Rejection

Note: (a) β = Path coefficient, SD = standard error, VIF = variance inflation factor, f^2 = size effect (b) The R^2 = 62.8% for USE. The standardized root mean squared residual (SRMR) = 0.085

Table 5 Predictive performance of the PLS-SEM model. The table reports the Stone–Geisser Q² statistic and the results of the cross-validated predictive ability test (CVPAT)

		CVPAT: Benchmark is indicator average				CVPAT: Benchmark is parsimonious linear model			
Output	**Q²**	**ML**	**BL**	**ALD**	**p-value**	**ML**	**BL**	**ALD**	**p-value**
USE	58.6%	3.53	8.53	-5.00	<0.001	3.53	3.91	-0.38	0.133

Note: Q^2 stands for the Stone Greisser's measure from PLS-predict, ML = model loss, BL = benchmark loss, ALD = Average loss difference

Table 4 also shows no serious collinearity issues, as the Variance Inflation Factor (VIF) for all variables is below the threshold of 5. Concerning the significance of the hypothesized relationships outlined in Sect. 2, only two constructs show statistically significant effects. The influence of relativism has a path coefficient (β) of 0.398, a p-value (p) of 0.014, and an effect size (f²) of 0.060. The strongest influence is that of consequentialism, with a path coefficient (β) of 0.581, $p < 0.001$, and an effect size (f²) of 0.259.

Table 5 presents the predictive performance metrics of the model under both scenarios. The Stone–Geisser Q² value is 58.6%, indicating a high level of predictive relevance (Hair et al. 2019). The CVPAT analysis displayed in Table 5 shows that the proposed model outperforms both the indicator average (IA), with an average loss difference (ALD) of −5.00 ($p < 0.001$), and the linear model (LM), with an ALD of −0.38 ($p = 0.133$). However, only the superior performance relative to the indicator average is statistically significant.

Results of the fsQCA. Response of the research question 2

The first step in the fsQCA process aligns with that of PLS-SEM: verifying the internal consistency of the measurement scales, which is confirmed in Table 2. The second step involves calibrating the membership levels of the variables used in the analysis. The results of this calibration are presented in Table 6.

As shown in Table 6, for the constructs USE, MEQ, REL, CON, and DEO, the thresholds for complete membership, non-membership, and the crossover point were established based on standardized scores of latent variables. For the GEN variable, Boolean calibration was applied, where 1 represents female and 0 represents male. Employment status (JOB) was calibrated as follows: 1 for students with full-time

Table 6 Calibration thresholds used in the FsQCA

	USE	MEQ	REL	CON	DEO	GEN	JOB
nonmembership	-1.133	-1.16	-1.18	-1.269	-1.29	0	0
crossover point	-0.098	0.064	0.196	0.134	0.192	---	0.5
full-membership	0.937	1.105	0.978	1.019	1.179	1	1

Note: calibration thresholds correspond to full membership (1), crossover point (0.5), and full non-membership (0). For GEN, full membership indicates female and non-membership indicates male. For JOB, values represent full-time job (1), part-time or temporary job (0.5), and no job (0). For the outcome and ethical constructs, the values are standardized factor scores employment, 0.5 for those with part-time or temporary jobs, and 0 for students with no employment.

For example, as detailed in Table 6, the membership function of REL was constructed using the evaluation of the two items comprising this latent variable. The aggregate value of these items reflects the factor score, with the 15th percentile equal to −1.180, the median at −0.196, and the 85th percentile at 0.978. Thus, a highly favorable evaluation of REL corresponds to a factor score of 0.978 or above (indicating full membership = 1), while a completely unfavorable evaluation is below −1.180 (non-membership = 0). The crossover point (–0.098) represents a completely neutral position and is set at the 50th percentile (membership = 0.5). Between −1.180 and 0.937, the degree of membership (from 0 to 1) for each observation is determined linearly based on its REL factor score.

The necessary conditions analysis presented in Table 7 shows that no factor—whether present or absent—qualifies as a necessary condition for GenAI use (USE) or non-use (~USE). While the consistency values for REL and CON exceed the 0.8 threshold, they do not meet the 0.9 criterion required to be considered necessary conditions. Similarly, for the outcome of non-use, no condition—such as the negation of any ethical construct—reaches the required consistency level to be interpreted as necessary.

Furthermore, the results in Table 7 are consistent with the correlational hypotheses discussed in Sect. 2.1. Specifically, the presence of MEQ, REL, CON, and DEO exhibits higher consistency in explaining GenAI use (USE) than their absence, while the absence of these constructs (~MEQ, ~REL, ~CON, and ~DEO) shows higher consistency in explaining non-use (~USE). A similar pattern is observed for employment status, but not for gender: being female shows slightly higher consistency for USE, and being male for ~USE, which is not aligned with Hypothesis H5.

The determination of sufficient conditions is presented in Fig. 2. Regarding the solution for GenAI use, four configurations are obtained, with a consistency score of 0.84 and a coverage score of 0.78. All ethical constructs appear as a condition in at least one configuration. However, JOB and MEQ appear only as peripheral conditions.

The influence of the ethical constructs on GenAI use (USE) is unequivocally positive, as in all configurations where they appear, they must be present. This is the case for moral equity (present in two prime implicants, but always as a peripheral condition), relativism and deontology (each present in three configurations, always as core conditions), and consequentialism (present in two recipes, though a core condition in only one).

Regarding GEN, being female appears as a core condition in the configuration CON•GEN. Additionally, although employment status (JOB) appears in two configurations—which supports the hypothesis that being employed may facilitate GenAI use—it does so only as a peripheral condition.

Therefore, Proposition 1 can be accepted for all variables except for the conditions related to the gender factor.

Figure 2 identifies six paths in the solution related to the non-use of GenAI. The consistency of the solution is acceptable (0.87), and the coverage is 0.72. All ethical variables appear as conditions in more than one path, and—with the exception of

Table 7 Necessity analysis GenAI use and non-use

	USE		~USE	
Condition	consistency	coverage	consistency	coverage
MEQ	0.75	0.79	0.37	0.39
REL	0.82	0.78	0.35	0.38
CON	0.83	0.82	0.37	0.41
DEO	0.79	0.71	0.41	0.41
GEN	0.53	0.72	0.47	0.71
JOB	0.62	0.68	0.45	0.49
~MEQ	0.42	0.39	0.74	0.78
~REL	0.41	0.39	0.76	0.8
~CON	0.41	0.38	0.80	0.81
~DEO	0.47	0.46	0.71	0.78
~GEN	0.52	0.28	0.48	0.29
~JOB	0.51	0.47	0.47	0.79

Note: (a) The symbol "~" denotes an absence condition

	USE				~USE					
Path	1	2	3	4	1	2	3	4	5	6
MEQ		•	•						⊗	⊗
REL		●	●	●		⊗	⊗	⊗		⊗
CON	●	•		•			⊗	⊗	⊗	⊗
DEO		●	●	●	⊗	⊗	⊗	⊗	⊗	
GEN	●				⊗	⊗		⊗	⊗	•
JOB			•	•	⊗	⊗	⊗			
cover	0.59	0.58	0.42	0.42	0.13	0.13	0.46	0.17	0.18	0.49
cons	0.85	0.90	0.89	0.88	0.90	0.86	0.90	0.88	0.89	0.88
cover	0.78				0.72					
cons	0.84				0.87					

Fig. 2 Intermediate solution for use and non-use of GenAI. Note: (**a**) Circle • indicates the presence of a factor as a condition, circle ⊗ indicates the absence of a factor, and a blank indicates no relevance in the prime implicate. Large circles represent core conditions, and small circles represent peripheral conditions. (**b**) cov stands for coverage measure and cons for consistency

MEQ—each appears in at least one prime implicant as a core condition. Moreover, in all instances in which they appear, they do so as absences of the respective variable.

The absence of MEQ appears as a peripheral condition in two configurations. The absence of REL and CON appears as core conditions in four configurations, while the absence of DEO is a core condition in three configurations and a peripheral condition in two. Additionally, the absence of JOB appears as a condition in three configurations—serving as a core condition in two of them. This finding is consistent with Proposition 2.

Regarding GEN, it is included in five configurations. In four of these, being male is a core condition, and in one, being female appears as a peripheral condition. Therefore, Proposition 2 is supported for all conditions in the solution paths—except those related to gender.

It can also be observed that the prime implicants in the solutions for GenAI use and non-use are not symmetrical. While the solution explaining GenAI use has broader coverage, the solution for non-use shows higher consistency. Furthermore, the number of configurations identified for explaining the intention to use versus not to use GenAI is different. Similarly, the specific configurations leading to use and non-use are not mirror images. For instance, in Fig. 2, the first configuration associated with USE is CON•GEN; however, in the solution for ~USE, there is no symmetrical prime implicant such as ~CON•~GEN.

Additionally, some variables exhibit relatively symmetrical behavior as conditions for both USE and ~USE, while others do not. For example, MEQ appears as a peripheral condition when present in USE and when absent in ~USE. DEO and REL are the most frequent core conditions—present in USE and absent in ~USE—showing a relatively symmetrical pattern. In contrast, variables such as CON, GEN, and JOB appear less frequently in the configurations leading to use (always with their presence) than in those leading to non-use (with their absence).

Therefore, the behavior of these factors as conditions for USE and ~USE is asymmetrical, which supports the acceptance of Proposition 3.

Discussion

Overall discussion

This study set out to examine how higher education students ethically assess the intensive use of generative artificial intelligence (GenAI) in the production of gradable academic essays, using both correlational and configurational perspectives. To this end, two research questions were posed. The first (RQ1) investigated the overall impact of different ethical dimensions—moral equity, relativism, consequentialism, and deontology—as well as sociodemographic variables (gender and employment status) on the intention to use GenAI. The second (RQ2) examined how specific combinations of those variables configure distinct profiles of users and non-users, using fsQCA.

Regarding RQ1, the PLS-SEM model demonstrated strong explanatory (over 60% of variance explained) and predictive capacity, supporting the robustness of the results. Only two ethical dimensions, relativism and consequentialism, had a significant link with the intention to use GenAI.

Consequentialism emerged as the strongest predictor, indicating that many students assess this practice mainly based on the personal benefits they might obtain: time optimization, reduced stress, improved grades, or compatibility with work obligations. This logic aligns with utilitarian or egoistic approaches, where the moral value of an action depends on its perceived consequences. This finding is consistent with research in technology adoption frameworks that highlight the role of perceived usefulness and effort expectancy in GenAI adoption in education (Al Darayseh 2023; Al-Okaily 2025; Panggabean and Silalahi 2025; Sobaih et al. 2024; Strzelecki 2024), as well as with hedonistic motives (Strzelecki et al. 2024). Within the MES framework, consequentialism—especially in its utilitarian form—has also been found to be the most significant ethical basis in student behaviors such as plagiarism (Jung 2009; Prashar et al. 2024; Yang 2012) and falsifying recommendation letters (Leonard et al. 2017).

Relativism also showed a statistically significant impact, suggesting that the social context—including implicit norms, peer behavior, and perceived acceptability—plays a decisive role in the decision to use GenAI. This finding aligns with the peer cheating effect, and with prior research on relativism as a key factor in the acceptance of practices like software piracy, privacy violations (Jung 2009), or collaborative chats in forbidden group settings (Yang 2012). It also corresponds to technology acceptance models that highlight the role of social influence in GenAI adoption among both students (Amin et al. 2025; Elshaer et al. 2024; Sobaih et al. 2024) and teachers or researchers (Strzelecki et al. 2024).

In contrast, moral equity and deontology did not show statistically significant effects in the correlational model. In the case of moral equity, this may be because, although many students acknowledge that using GenAI can violate principles of justice or moral duty, such criteria are not necessarily decisive when making practical decisions under academic pressure or in contexts of normative ambiguity. Moral equity often operates as an abstract ethical orientation, but when students face concrete dilemmas, such as whether to use GenAI in writing assignments, instrumental considerations (e.g., performance, time constraints, or perceived risks of detection) may outweigh abstract notions of fairness. In other words, while students can cognitively recognize the justice implications of their behavior, these concerns may not be sufficiently salient to restrain misconduct. This result is consistent with findings on the lack of relevance of moral justice in explaining cheating in placement essays and in chat rooms during supervised exams (Leonard et al. 2017).

The lack of significance of deontological judgments has also been reported in previous studies on plagiarism (Jung 2009; Leonard et al. 2017) and placement essay fraud (Leonard et al. 2017). A plausible explanation in our paper is that, given the novelty of GenAI technologies, their use is still far from being fully regulated, partly due to the limited experience of educators with these tools (Licht 2024). This normative indeterminacy prevents the establishment of clear "contracts," leaving students uncertain about which GenAI practices are academically inappropriate (Burrus et al. 2007). Evidence from U.S. universities highlights the absence of robust and consistent frameworks on ethics, intellectual property, privacy, and the long-term pedagogical implications of GenAI (McDonald et al. 2025). Even within leading institutions, instructors often have the autonomy to decide how to regulate AI in their courses. While this discretion fosters innovation, it also generates uneven experiences for students (Alqahtani and Wafula 2025). Such variability may account for the absence of clear contractual references, which in turn explains why deontology did not emerge as a statistically significant predictor in this study.

Similarly, gender and employment status did not exhibit a significant link with intention to use GenAI in the correlational model. Although literature suggests that gender may influence ethical decisions (Nguyen et al. 2008), many empirical studies report subtle or non-significant differences (Yang 2012).

However, when RQ2 is analyzed through a configurational perspective using fsQCA, complementary and more nuanced findings emerge. The solutions for both use and non-use demonstrate excellent consistency (>0.8) and coverage (>0.7). Thus, the application of MES using fsQCA provides strong empirical performance in this context.

Four distinct combinations of conditions were identified as leading to the intention to use GenAI, revealing that this behavior does not stem from a single ethical logic or user profile. These configurations include the presence of moral equity, relativism, deontology, and/or consequentialism—supporting the hypothesized positive association of these ethical evaluations with GenAI use. The presence of work obligations appears in multiple paths, though as a peripheral condition. This supports the idea that balancing work and study may facilitate GenAI use in ethically questionable ways.

Interestingly, however, in the configurations where gender appears, it is associated with being female—contradicting the hypothesis that women are generally more reluctant to engage in ethically questionable behavior.

The absence of relativism, consequentialism, and deontology appears as a core condition in several configurations that lead to non-use, supporting the directional hypothesis between ethical judgments and intention to use GenAI. Likewise, not having work obligations is also a relevant condition.

In both use and non-use configurations, being male appears more frequently—again contradicting the idea that women are more ethically strict in academic contexts. The fact that statistical differences in the intention to use GenAI between male and female students are not significant, while the configurational analysis suggests that women may currently be more prone to its use, could appear to contradict the common finding that women tend to behave more ethically than men. However, this apparent inconsistency can be explained in two ways. First, students do not perceive clear rules regarding GenAI use, and since women are more likely to base their decisions on explicit norms (Pilcher and Smith 2024), the absence of such norms may reduce their ethical barriers in this context. Second, women have been reported to achieve better academic performance than men (Tsaousis and Alghamdi 2022), a pattern that also applies to social science studies in Spain (Ministerio de Ciencia, Investigación y Universidades, 2024). This suggests that women may experience greater pressure to perform academically, and the perception of such pressure can act as a facilitator of engagement in ethically questionable practices (Clinciu et al. 2021; Rua et al. 2024).

Additionally, the fsQCA results confirm that the configurations explaining use and non-use are not mirror images of each other. This causal asymmetry, common in complex phenomena like technology adoption (Andrés-Sánchez et al. 2021; Arias-Oliva et al. 2024), shows that the factors driving rejection are not merely the absence of those driving adoption.

Taken together, these findings indicate that the decision to use GenAI in academic writing is shaped by a complex moral logic that intertwines personal values, contextual perceptions, and individual characteristics. The combined use of PLS-SEM and fsQCA proved especially effective in capturing both the global influence of variables and the diversity of ethical and sociodemographic profiles involved.

Theoretical implications

First, this study provides empirical evidence in the field of ethical judgment regarding emerging technologies in academic settings, extending the use of the Multidimensional Ethics Scale (MES) to the context of GenAI. While MES has been widely used in business and consumer contexts, its application to dishonest academic practices involving GenAI is a novel contribution. The findings confirm that ethical evaluations of GenAI use are not governed by a single moral perspective, but instead reflect multiple philosophical frameworks—validating the multidimensional nature of ethical judgment.

Second, the study contributes to academic ethics theory by showing that classical normative frameworks such as deontology or moral equity carry less weight than more contextual or utilitarian approaches. This suggests that students do not evaluate academic practices solely based on universal principles, but rather relativize their judgments according to context, pressure, or personal circumstances. Student ethics regarding AI must therefore be understood as situated and pragmatic, rather than strictly principled.

Third, the combined use of PLS-SEM and fsQCA offers methodological value for research in higher education and applied ethics. While PLS-SEM identifies the statistical strength of each variable's influence on intention, fsQCA uncovers causal configurations that explain differentiated profiles of adoption or rejection. This dual perspective helps overcome the limitations of traditional correlational models and aligns with recent calls in the literature for mixed-method and complexity-aware approaches to technology adoption and ethical behavior.

Implications in practice

The findings of this study carry important implications for universities, faculty, and educational policymakers. First, the findings highlight that perceived personal usefulness and social acceptance are the main drivers of intensive GenAI use—even in ethically questionable contexts. Educational institutions must recognize that honor codes or formal rules alone may be insufficient deterrents. Instead, a proactive strategy is needed—one that combines ethical training with the promotion of values such as authenticity, commitment, and self-regulation.

Second, the fact that GenAI use is configured through multiple causal pathways, including employment status, suggests that interventions should be tailored to student diversity. For instance, students balancing work and study may resort to GenAI out of necessity rather than intent to deceive. In such cases, flexible academic support policies—like deadline extensions, personalized tutoring, or academic counseling—could be more effective. There is no one-size-fits-all measure to discourage GenAI misuse; rather, a range of measures may be more or less effective depending on the student profile.

One desirable solution would be for GenAI tools to incorporate digital signatures in their outputs, enabling educators to identify AI-generated content without relying on unreliable detectors or subjective reporting (Shaw 2025). Developers (e.g., OpenAI, Google) also bear ethical and technical responsibility for implementing safeguards—such as warnings or restrictions against requests that violate academic norms (Shaw 2025).

Faculty, institutions, and legislators must also design meaningful learning tasks that foster autonomy rather than merely assess superficial results (Aylsworth and Castro 2024). In the social sciences, a responsible pedagogical integration of GenAI requires complex, contextual assessments that limit misuse, promote GenAI as a support tool, and demand transparency—e.g., through prompt disclosure. It also calls for incorporating ethical and cultural debates in the classroom about GenAI's biases and limitations (Reimer 2024). In this regard, moral education through concrete examples and real-life applications has proven to be an extremely effective tool for promoting ethical awareness and decision-making (Han 2025).

Finally, institutions must adopt clear, explicit policies on GenAI use and implement formal monitoring and sanction mechanisms. Responsible use of GenAI in higher education cannot rely solely on technical regulation, but must be grounded in cross-cutting ethical education (Aler Tubella et al. 2023). Students and faculty must be trained not only as technical users but as citizens capable of developing, assessing, and applying GenAI ethically and responsibly (Batista et al. 2024).

Ultimately, the study highlights the importance of fostering a culture of academic integrity, where ethics is not limited to rule compliance but forms part of comprehensive training. This includes both formal instruction and opportunities for deliberation around real-life dilemmas, encouraging students to engage in reasoned, reflective positioning (Cunha et al. 2016).

Conclusions

Main findings

The paper examined the ethical judgment made by university students concerning using generative artificial intelligence (GenAI) for academic essay writing. It explored both the global influence of ethical and sociodemographic variables using a correlational approach, and the causal configurations underlying students' decisions through fsQCA. By combining PLS-SEM and fsQCA, the study provides robust answers to both research questions.

First, the findings confirm that not all ethical dimensions have the same explanatory power. Consequentialism emerged as the main determinant of the intention to use GenAI, followed by relativism. This suggests that students' decisions are driven less by normative principles (such as moral duty or justice) and more by expected personal benefits and what they perceive as socially acceptable within their peer environment. In contrast, moral equity and deontology did not exhibit statistically significant effects. Regarding moral equity, this may reflect a disconnection between abstract ethical judgments and practical decision-making under conditions of academic pressure. As for deontology, its lack of significance may be explained by the normative ambiguity that currently surrounds the use of GenAI in academic contexts.

The configurational logic reveals that the intention to use or reject GenAI is explained by multiple causal pathways, in which various combinations of ethical and sociodemographic factors lead to similar outcomes. This diversity of profiles contradicts the notion of a single "typical" GenAI user and underscores the contingent and contextual nature of ethical judgment in academic scenarios.

The study also confirms the asymmetry between the configurations that explain GenAI use and those that explain its rejection. This means that the factors that drive adoption are not merely the absence of those that drive rejection, and vice versa. Such asymmetry highlights the complexity of the phenomenon and reinforces the value of configurational methods for capturing it.

Although sociodemographic variables did not show significant effects in the PLS-SEM model, job status and gender did play a relevant role in some causal configurations, particularly among non-user profiles. This finding suggests that their influence is not linear or uniform, but rather context-dependent, shaped by the ethical frameworks in which students are situated. In fact, the configurational analysis suggests that the absence of clear rules on how to use GenAI in the university setting, combined with the potentially greater pressure on women to perform, may give rise to gender-specific profiles that are more prone to its use.

Limitations of the study

This study presents several limitations that should be acknowledged. A key limitation is its reliance on a single-country dataset with a modest sample size. While not optimal, it should be noted that previous research applying the MES has also relied on relatively small samples (e.gJung 2009; Leonard et al. 2017; Shawver and Sennetti 2009), and from the perspective of the analytical tools employed, the size of our sample is acceptable. Moreover, the sample consists exclusively of social science students from a couple of Spanish higher education institutions, which restricts the applicability of the findings to other cultural, geographical, or disciplinary settings. Ethical perceptions of GenAI use may differ substantially among students in engineering, health sciences, the arts, or other domains, as well as in countries where institutional policies toward these technologies are either stricter or more permissive. It should also be emphasized that the findings of this study may prove useful for subsequent reviews and meta-analyses, enriching comparative analyses across countries, disciplines, or cultures.

From a statistical perspective, our sample is comparable to those studies and adequate to support the analyses conducted. With regard to gender differences, while the configurational results suggesting a greater propensity among women to use GenAI might appear to contradict the traditional view that women behave more ethically than men, this inconsistency highlights an important research avenue. Rather than being "less ethical," women may operate according to different ethical patterns, particularly under academic pressure or normative ambiguity.

The study relies on a hypothetical scenario in which students are under academic pressure and use GenAI extensively. While this approach standardizes responses, it may not accurately reflect students' actual behavior in real-life contexts. Thus, a potential intention–behavior gap may exist.

Finally, the study does not incorporate other potentially relevant explanatory variables, such as technological familiarity, academic performance, perceived stress levels, or the clarity of institutional policies, all of which could influence student decisions.

Moreover, the study relies on cross-sectional survey data, capturing a "snapshot" of students' ethical perceptions at a specific point in time—during an early phase in the implementation and regulation of GenAI in higher education. While this is useful for identifying early trends and emerging attitudes, it does not allow for an analysis of how these perceptions may evolve. Future research should adopt longitudinal approaches to examine the trajectory of ethical judgment over time, offering a more dynamic and contextualized view of GenAI's risks, benefits, and acceptability at different stages of academic integration.

Future research directions

Based on these limitations, several future research avenues emerge that could broaden and deepen understanding of applied ethics related to GenAI in higher education.

First, it would be valuable to replicate this study in other educational and cultural contexts, across various academic disciplines and universities in different countries. This would enable comparisons of ethical judgment patterns and adoption strategies, and allow for an assessment of the universality or cultural specificity of the phenomenon.

Second, future studies could use longitudinal or experimental designs to observe how ethical judgments and actual behaviors evolve in response to GenAI use. This would allow for a clearer contrast between declared intentions and real actions, and help analyze the influence of time, evaluation type, or institutional communication.

Third, incorporating additional variables such as technical knowledge of AI, academic self-efficacy, perceived time pressure, or clarity of institutional policies regarding GenAI would help develop more comprehensive models that capture cognitive, emotional, and structural dimensions of ethical decision-making.

With regard to gender differences, although the configurational results suggesting a greater propensity among women to use GenAI might seem to contradict the traditional view that women behave more ethically than men, this inconsistency opens an important line of inquiry. Rather than indicating that one gender is "less ethical," the evidence may suggest that men and women operate according to different ethical patterns, particularly when facing academic pressure or normative ambiguity. Future studies should therefore investigate the potential moderating role of gender in the relationship between ethical dimensions and academic decision-making, using larger and more diverse samples to validate and extend these findings.

Finally, future research could explore the impact of ethics-based educational interventions to assess whether guided reflection on moral dilemmas—such as the use of GenAI—modifies students' attitudes and behaviors. In a context where AI is increasingly embedded in educational processes, fostering a situated, critical, and deliberative ethical mindset becomes a central pedagogical objective.

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Data availability The data supporting the analysis is available upon reasonable request.

Code availability Not applicable.

Declarations

Institutional review board (1) All participants received detailed written information about the study and procedure; (2) no data directly or indirectly related to the health of the subjects were collected, and therefore the Declaration of Helsinki was not mentioned when informing the subjects; (3) the anonymity of the collected data was ensured at all times; (4) the research received a favorable evaluation from the Ethics Committee of a researchers' institution (CE_20250710_10_SOC).

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