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Student engagement with generative AI in Greek higher education: Use patterns and academic integrity concerns

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ABSTRACT

This study explores how undergraduate students in Greek public universities engage with generative AI tools for academic purposes and how such use relates to perceptions of reliability, ethical concerns, and academic integrity. Although interest in AI in higher education has grown rapidly, empirical evidence from non-Anglophone European systems, and from Greece in particular, remains scarce, leaving an evidence gap that this study addresses. Data were collected from 442 students across five institutions using an original questionnaire with demonstrated content validity and high internal consistency. Results indicate moderate but growing use of AI, primarily for comprehension support, problem-solving, and information retrieval. While students recognise the functional benefits of AI, they express reservations about its reliability and strong concerns regarding its potential to facilitate academic misconduct, including plagiarism. Correlational and regression analyses suggest that increased use of AI coexists with, rather than diminishes, ethical awareness. Cluster analysis identifies distinct user profiles, reflecting varying levels of engagement and ethical sensitivity. Overall, the findings highlight the dual role of generative AI as both a learning aid and a challenge to academic integrity, underscoring the need for institutional guidelines and ethical frameworks.

Keywords: artificial intelligence, higher education, academic integrity, ethical concerns, student perceptions

INTRODUCTION

Decades earlier, Alan Turing predicted that by the twentieth century's end, intelligent machines would be indistinguishable from humans. This prediction is reflected in today's online chatbots, which emulate human conversation through textual or verbal exchanges for a plethora of purposes, including educational services (Davis, 2024). In recent years, artificial intelligence (AI) applications—most notably generative language models such as ChatGPT—have become increasingly embedded in higher education (Bond et al., 2024; Holmes et al., 2019; Selwyn, 2019). These tools are now routinely used by students to support information retrieval, text production, and problem-solving, and they are often framed as powerful resources for deepening understanding and enhancing academic productivity (Ipek et al., 2023; Jereb & Urh, 2024; Luckin et al., 2016; Ma et al., 2014). At the same time, universities are confronted with substantial ethical and pedagogical challenges: AI-assisted work may obscure authorship, facilitate plagiarism, and weaken students' capacity for autonomous critical thinking (Cotton et al., 2024; Oravec, 2023; Rane et al., 2024). As a result, higher education institutions are under pressure to design policies that both enable innovation and safeguard academic integrity (Bearman et al., 2023; Zawacki-Richter et al., 2019).

According to Butson and Spronken-Smith (2024), situated at the crossroads of technological advancement and academic inquiry, the growing power of AI constitutes a critical juncture for higher education research. It is not merely about supplementing research with sophisticated tools; rather, AI is beginning to disrupt traditional research methodologies, ethical norms, and core principles that have long underpinned scholarly practice. In the end, is the use of artificial intelligence in higher education a panacea, or a "Pandora's can of worms", as provocatively suggested by Miller (2024)?

Conceptually, this study is informed by sociological perspectives that treat educational processes as socially constructed and mediated by technologies. Drawing on critical theories of technology, and especially Feenberg's work, which emphasises that technologies are not neutral instruments but sociotechnical systems shaped by power relations, institutional logics, and value conflicts, AI is approached as a sociotechnical system whose design and use are shaped by institutional norms, power relations, and competing value frameworks (Feenberg, 1995, 2002, 2017). This perspective allows us to examine not only how often students use AI and for which tasks, but also how they position themselves ethically and pedagogically vis-à-vis AI in academic work.

Empirically, the study focuses on four domains of AI-mediated academic activity: (a) information retrieval, (b) comprehension of learning materials, (c) analytical problem-solving, and (d) practices that may violate academic integrity, such as plagiarism or bypassing assessment rules (Cotton et al., 2024; Oravec, 2023). It further explores how perceptions of AI reliability, ethical concerns, and support for regulatory policies relate to students' reported willingness to engage in AI-enabled misconduct. Finally, the analysis examines whether distinct user profiles can be identified and how these are associated with demographic characteristics such as gender and field of study, in line with previous findings that highlight gendered differences in risk perception and ethical sensitivity in AI use (Infante Rivera et al., 2024).

Although this debate is global, its national articulations differ. In the Greek higher education context, the available evidence is still emerging and has so far concentrated on the antecedents of adoption rather than on the ethical negotiation of AI use. Lavidas et al. (2024), for instance, found that performance expectancy, habit, and enjoyment were the key determinants of intention to use AI applications among students of the humanities and social sciences, while Kostas et al. (2025) reported that Greek students recognise the productivity benefits of ChatGPT yet voice concerns about reliability, ethics, and the erosion of critical thinking. These contributions are valuable, but they leave largely unexamined how patterns of use, trust, and ethical orientation jointly relate to concerns about misconduct and to support for institutional regulation—the focus of the present study.

By integrating a theoretically grounded sociotechnical perspective with quantitative survey data from Greek universities, the study aims to offer an evidence-based account of AI adoption in higher education. The findings are intended to inform institutional policies and pedagogical strategies that foster responsible AI use, support AI literacy, and uphold academic integrity in rapidly evolving digital learning environments (Bond et al., 2024; Holmes et al., 2019; Tuomi, 2023; Yu & Yu, 2023).

LITERATURE REVIEW

Artificial intelligence applications, and notably ChatGPT, have become central to widespread discussions regarding their role in education and scholarly writing, both in academic circles and on social media. The review below is organised thematically, in line with the research questions: it first considers the functions and adoption of generative AI in higher education, then students' perceptions, trust, and ethical concerns, followed by issues of academic integrity, demographic variation in adoption, and finally the Greek higher education context, where the research gap addressed by this study is located.

Generative AI in Higher Education: Functions and Adoption

AI has significantly transformed academic research, serving as a driving force behind both methodological innovations and broader changes in scholarly paradigms (Pal, 2023). Despite the impressive capabilities of these systems, however, educational institutions have lagged in evolving their culture and curricula to accommodate the implications of such technological innovations (Brynjolfsson & McAfee, 2014). Broader reviews of the field observe that AI is being incorporated into teaching, learning, and research across higher education, even as its pedagogical role and boundaries remain under negotiation (Arora, 2021; Shen et al., 2021). For university students navigating the demands of academic writing and research, AI systems have rapidly become accessible assistants in learning and productivity. Initially, the advent of generative AI led most educational institutions to ban its use, treating any student interaction with these technologies as cheating subject to disciplinary action; gradually, though, numerous institutions have come to recognise generative AI as a resource for promoting learning rather than merely a potential violation of academic integrity (Hashmi & Bal, 2024).

Students' Perceptions, Trust, and Ethical Concerns

A rapidly growing body of empirical research has begun to document how students perceive and use generative AI tools, as well as the ethical dilemmas they raise. Several large-scale studies have examined students' early reactions to these systems, although each illuminates a distinct facet of the phenomenon. Gasaymeh et al. (2024) focused specifically on students' insights into generative AI writing tools, highlighting both their perceived usefulness and concerns about over-reliance. Johnston et al. (2024) documented students' perspectives on the use of generative AI in higher education, emphasising tensions between convenience and integrity. Ravšelj et al. (2025) provided the most comprehensive global evidence to date, surveying more than 20,000 students across more than 100 countries and finding broad endorsement of AI's utility for summarising and brainstorming alongside widely shared concerns about cheating and the need for regulation. Sousa and Cardoso (2025) likewise reported substantial use of generative AI among higher education students, coupled with uncertainty about acceptable practice.

Views on generative AI tools such as ChatGPT are therefore mixed: some accounts highlight the enhanced accessibility and convenience they offer for learning, whereas others raise concerns about potential cheating and threats to academic integrity in the absence of clear regulations (Ravšelj et al., 2025). The release of ChatGPT has triggered notable anxieties about academic integrity across the higher education sector. Yet some scholars maintain that generative AI tools can effectively enhance students' learning experiences and propose that educators adjust their pedagogical and assessment practices to reflect the contemporary context in which AI is openly available (Sullivan et al., 2023).

Academic Integrity and the (Mis)use of Generative AI

Universities worldwide have consistently expressed concern over academic misconduct, and the emergence of generative AI has intensified this issue, particularly through practices such as plagiarism, cheating, fabrication, and the gaining of an unfair advantage (Currie, 2023; Song, 2024). Other work has focused more specifically on student (mis)use of generative AI for university-related tasks, differentiating between legitimate support and practices that conflict with assessment rules (Reiter et al., 2025). Findings further suggest that students experience uncertainty regarding the threshold at which AI-generated content is considered academically dishonest, a challenge exacerbated by insufficient guidance and instruction on ethical AI practices (Alghalbie et al., 2026).

At the same time, evidence points to important differences across national, institutional, and disciplinary contexts. These contributions are complementary rather than interchangeable: Bearman et al. (2023) offered a critical review of the discourses through which AI is constructed in higher education; Bond et al. (2024) conducted a meta-systematic review calling for greater attention to ethics, collaboration, and methodological rigour; Chu et al. (2022) mapped the roles and research trends of AI in higher education through a systematic review of highly cited work; and Zawacki-Richter et al. (2019) drew attention to the conspicuous absence of educators from much of the AI-in-education literature. Together they indicate that regulatory frameworks and prevailing cultures of academic integrity vary substantially across settings.

Demographic Variation in AI Adoption

Beyond aggregate patterns, a growing strand of research indicates that engagement with AI is socially and demographically differentiated. Gendered differences in risk perception and ethical sensitivity have been reported, with women tending to express greater caution regarding the ethical implications of technology use (Infante Rivera et al., 2024). Determinants of adoption also vary with prior experience and habit: in a Greek sample, Lavidas et al. (2024) found that performance expectancy, habit, and enjoyment were the strongest predictors of students' intention to use AI applications—the proximal determinant of behaviour in established models such as the theory of planned behaviour (Ajzen, 1991)—suggesting that adoption is shaped by accumulated practice rather than distributed uniformly across the student population. Such variation implies that students' socioeconomic and cultural background—including indicators of family cultural capital (Bourdieu, 1986), such as parental education—may condition both the extent of AI use and the ethical frames students bring to it, a possibility that remains underexplored.

The Greek Higher Education Context and the Research Gap

Empirical knowledge about generative AI in Greek higher education is still in its early stages. The available studies have concentrated chiefly on the antecedents of adoption: Lavidas et al. (2024) modelled the behavioural intention to use AI applications among humanities and social sciences students, while Kostas et al. (2025) surveyed 515 students and reported a dual perspective in which the perceived benefits of ChatGPT for research efficiency and personalised learning coexisted with concerns about reliability, ethics, and declining critical thinking. These works establish that Greek students are active adopters with ambivalent attitudes, but they do not examine how patterns of use, perceived reliability, and ethical acceptability jointly relate to concerns about misconduct and to support for institutional regulation. More broadly, the international evidence base remains uneven: most studies have been conducted in Anglophone or global samples, and systematic knowledge about how students in non-Anglophone European systems, such as Greek higher education, interpret and govern their relationship with AI tools in everyday academic practice is still limited. The present study addresses this gap directly, and on the basis of documented empirical evidence rather than assumption.

Research Aims and Questions

With the rapid diffusion of tools such as ChatGPT across universities, interest has grown in how students incorporate these technologies into their coursework. AI tools can accelerate literature searches, help unpack difficult texts, and generate ideas, but they also raise concerns about plagiarism, fairness, and academic integrity. Despite their increasing use, relatively few studies have examined, in a systematic way, how students' trust in AI, their perceptions of ethical acceptability, and their patterns of use relate to their concerns about misuse and their support for institutional regulation, particularly in the Greek context. Demographic factors—including gender, age, field of study, and socioeconomic background—may also shape these views and habits, yet remain understudied. Addressing these gaps is essential for developing policies and ethical guidance that reflect actual practice in higher education.

Accordingly, the study is guided by the following research questions, which are aligned with the structure of the instrument (Scales A–E) and with the analyses reported below:

- **RQ1.** To what extent do students use AI tools for academic purposes, specifically for the search of educational resources (Scale A), the understanding of educational material (Scale B), and the solving of academic problems (Scale C)?
- **RQ2.** How do students perceive the reliability and the ethical acceptability of AI tools in educational contexts?
- **RQ3.** How are frequency of AI use, familiarity, perceived reliability, and perceived ethical acceptability associated with the academic uses of AI captured by Scales A–C?
- **RQ4.** To what extent do demographic and educational background variables (gender, age, field of study, parental education, residence, and perceived family financial situation) relate to students' academic use of AI tools?
- **RQ5.** Which factors are associated with students' concerns about ethical risks and the potential misuse of AI tools for cheating on exams and assignments (Scale D)?

Table 1. Demographic and social characteristics of the sample (N = 442)

Characteristic	n	%
Gender		
Male	73	16.5
Female	369	83.5
Age (Years)		
18–20	87	19.7
21–22	256	57.9
> 23	99	22.4
Field of studies		
Humanities and Social Sciences	378	85.5
Economics and Administration	6	1.4
Science	26	5.9
Technology	7	1.6
Health	2	0.5
Other	23	5.2
Area of residence		
Large urban complex	127	28.7
Urban area	161	36.4
Semi-urban area	101	22.9
Rural area	53	12.0

Highest level of parental education (Father and Mother compared)

Education level	Father n	Father %	Mother n	Mother %
Compulsory education not completed	30	6.8	16	3.6
Compulsory education graduate	79	17.9	63	14.3
Secondary education graduate	112	25.3	98	22.2
Post-secondary vocational education	87	19.7	82	18.6
University degree	99	22.4	136	30.8
Master's or PhD graduate	35	7.9	47	10.6

Note. Percentages are column percentages within each characteristic. Parental education is reported in parallel for fathers and mothers to permit direct comparison; it is included as an indicator of family cultural capital (cf. Section *Demographic variation in AI adoption*).

RQ6. To what extent do students support institutional regulation and transparency in the use of AI tools (Scale E), and which factors are associated with this support?

RQ7. Are there significant gender or other demographic differences in ethical concerns (Scale D) and in support for AI regulation (Scale E)?

These questions are grounded in the theoretical framework outlined above, which conceptualises students' engagement with AI as part of their broader rapport with knowledge and as situated within sociotechnical and policy contexts that shape academic integrity in AI-rich learning environments.

MATERIALS AND METHODS

Participants and Sampling

The target population consisted of undergraduate students enrolled in five large public universities in Greece. Data were collected via an online questionnaire administered during the 2024–2025 academic year. Approximately 2,500 invitations were disseminated through institutional mailing lists, course announcements, and student networks. In total, 442 students completed the survey, yielding a response rate of about 17.7%.

The five participating universities were purposively selected to capture variation in institutional setting: two are located in major metropolitan centres of Greece, while the remaining three are situated in smaller urban areas. Within each institution, the questionnaire was administered to students attending courses taught by the instructors collaborating in the research. These courses are elective offerings taken by students from a range of disciplines, which broadened the disciplinary composition of the sample beyond any single department or faculty. A non-probability convenience sampling strategy was therefore employed, complemented by elements of snowball (chain-referral) sampling: initial participants were recruited through instructors and student representatives and were then encouraged to forward the survey link to peers in their academic and social networks. This approach facilitated access to students across different universities and study programmes but does not permit claims of statistical representativeness.

The sample size is adequate for the planned multivariate analyses (factor analysis, regression, clustering, and path analysis). However, given the non-probability sampling strategy and the overrepresentation of women and of students from the humanities and social sciences, the findings should be interpreted as indicative of patterns within this group rather than as fully generalisable estimates for the entire Greek university student population. The demographic and social composition of the sample is reported in **Table 1**.

As shown in **Table 1**, the vast majority of respondents were women (83.5%), and most were enrolled in the humanities and social sciences (85.5%), with smaller subsamples from the sciences, technology, economics and administration, health, and other fields. Just over half of the participants (57.9%) were 21–22 years old, with additional groups aged 18–20 (19.7%) and over 23 (22.4%). Students came from diverse residential contexts and family educational backgrounds, ranging from incomplete compulsory education to postgraduate degrees. Parental education was recorded for both parents because it is a well-established indicator of family cultural capital (Bourdieu, 1986); including it allows the analysis to examine whether the adoption of AI and the associated ethical orientations are socially stratified (cf. Section *Demographic variation in AI adoption*).

Ethical considerations

Participation in the study was voluntary and based on informed consent. Prior to completing the questionnaire, students were presented with an information note outlining the purpose of the study, the voluntary nature of participation, the anonymity and confidentiality of their responses, and the intended use of the data for research purposes. Only respondents who, having read this information, agreed to take part proceeded to the questionnaire. No personally identifying information was collected, and respondents could discontinue their participation at any point before submission. The data were processed and stored exclusively in anonymised form.

Instrument

Data were collected using a structured questionnaire developed specifically for the purposes of this study. The instrument was not adapted from a pre-existing scale; rather, its items were generated by the research team to operationalise the functional and ethical domains of AI-mediated academic activity identified in the literature reviewed in Section *Literature Review* (information retrieval, comprehension, problem-solving, academic integrity, and ethics/regulation). The questionnaire comprised three sections:

1. **Demographic and social characteristics (6 items).** This section captured respondents' gender, age, field of study, parents' educational level, area of residence, and perceived family financial situation.
2. **General AI use and perceptions (4 items).** Students reported how often they use AI tools such as ChatGPT, how familiar they feel with such tools, how reliable they consider AI-generated information to be, and how ethical they perceive the use of AI tools in education and academic work. Responses were given on five-point Likert-type scales (e.g., from 1 = "never" to 5 = "very often", or from 1 = "not at all" to 5 = "very much").
3. **Attitude and practice scales (5 scales, 10 items each).** The main body of the questionnaire consisted of 50 items grouped into five multi-item scales, each scored on a five-point Likert scale (1 = strongly disagree to 5 = strongly agree).

The five scales captured the following domains:

- **Scale A – Search for educational resources:** use of AI tools to locate, access, and filter academic materials (e.g., journal articles, textbooks, online resources).
- **Scale B – Understanding of educational material:** use of AI tools to clarify difficult concepts, obtain explanations, and generate summaries that support comprehension and study.
- **Scale C – Solving problems in various aspects of university studies:** use of AI tools for problem-solving, idea generation, and support with demanding academic tasks.
- **Scale D – Cheating on exams and assignments:** perceptions of the extent to which AI tools facilitate plagiarism, copying, and other forms of academic misconduct, as well as students' own temptation or perceived pressure to engage in such practices.
- **Scale E – Ethical issues and regulation:** attitudes towards ethical risks, the need for transparency, and support for institutional regulation and educational initiatives regarding AI use in academia.

Scale development followed a two-phase validation process. In the first phase, four experienced researchers in education and educational technology independently reviewed the initial pool of items for each scale, assessing content relevance, clarity, redundancy, and alignment with the theoretical constructs. Based on their feedback, problematic items were reworded, merged, or removed, and the final set of ten items per scale was agreed upon through discussion. In the second phase, content validity was evaluated quantitatively by a panel of ten experts using established indices (Zamanzadeh et al., 2014). Experts rated each item in terms of necessity and relevance, enabling computation of the content validity ratio (CVR) (Lawshe, 1975), the item-level and scale-level content validity indices (I-CVI and S-CVI), and a modified Cohen's Kappa statistic for inter-rater agreement. Cohen (1960) is cited here as the original source of the Kappa coefficient, on which the inter-rater agreement procedure is based, together with subsequent refinements and applications of the statistic (Smeeton, 1985; Uebersax, 1987; Strijbos et al., 2006). The resulting Kappa value of 0.79 indicates substantial agreement among experts regarding the adequacy and relevance of the items.

Prior to the main administration, the instrument was piloted with a small sample of approximately 30 students drawn from the target population. The pilot served to assess the clarity and comprehensibility of the items and the time required for completion; it led to minor refinements in wording, and the preliminary reliability of the scales was supportive. Given the limited size of the pilot sample, these results were treated as indicative and were not used to draw definitive psychometric conclusions; the full psychometric properties of the scales, including internal consistency and factor structure, are reported in *Results* section on the basis of the complete sample.

For the main analyses, item responses were averaged to produce scale scores for Scales A–E. Higher scores reflect more frequent or more positive endorsement of the respective domain (e.g., more extensive use of AI for resource search in Scale A; stronger agreement that AI facilitates cheating in Scale D; stronger support for ethical safeguards and regulation in Scale E).

Data Analysis

Data analysis proceeded in several steps using standard statistical software. First, descriptive statistics (frequencies, means, standard deviations) were computed for all demographic variables, the general AI use items, and Scales A–E. Second, the dimensionality and internal consistency of the five attitude scales were examined. Because all five scales were newly developed for this study, separate principal component analyses (PCA) were conducted for each scale to explore its underlying structure, with factor retention guided by eigenvalues greater than one, scree-plot inspection, and the interpretability of the solution. In all cases a single dominant component emerged, supporting the treatment of each scale as unidimensional. Although common-factor methods are often recommended for modelling latent constructs, principal components analysis is widely used as an initial exploratory technique in scale development and provided an adequate approximation for assessing the internal structure of the short attitude scales used here. Internal consistency was assessed using Cronbach's alpha computed separately for each scale; the coefficients ranged from 0.828 to 0.935 (reported per scale in **Table 3**), indicating high reliability for every construct.

Third, group differences were explored. Independent-samples t-tests (Welch's correction) were used to compare mean scale scores between men and women, after checking homogeneity of variance with Levene's test, and one-way ANOVA was applied to examine differences across other demographic categories (e.g., age groups, field of study), followed by post-hoc tests where appropriate. Fourth, associations between the general AI perception items and the five scales were examined using Spearman's rho correlations, given the ordinal nature of the items and the non-normal distribution of some variables. Fifth, a series of multiple linear regression models were estimated, with scale scores serving as dependent variables in turn and other scales and general

Table 2. General AI use and perceptions (item means and standard deviations)

Item	Mean	S.D.
How often do you use AI tools (e.g., ChatGPT)?	2.81	1.08
How familiar are you with AI tools?	3.11	1.03
How reliable do you consider AI-generated information to be?	3.00	0.79
How ethical do you consider the use of AI tools in academic work?	2.60	1.01

perception items entered as predictors; given the cross-sectional design, these regressions are interpreted in terms of associations rather than causal effects. Sixth, K-means cluster analysis was employed to identify distinct profiles of AI users based on the five scale scores, with the optimal number of clusters evaluated using the silhouette index for solutions with two to nine clusters; chi-square tests and ANOVA were then used to examine associations between cluster membership and demographic variables. Finally, an exploratory path analysis was conducted using scale scores as observed variables to model potential pathways linking different types of AI use to ethical concerns and regulatory attitudes; standardised regression coefficients (β) were estimated, and the model is treated as exploratory and heuristic rather than as a definitive causal model.

RESULTS

The results are organised so as to follow the research questions. Section *General AI Use and Perceptions (RQ2)* reports general AI use and perceptions, including perceived reliability and ethical acceptability (RQ2); Section *Academic Uses of AI: Scale Properties and Levels (RQ1)* reports the psychometric properties and the levels of the five attitude scales, addressing the extent of academic AI use (RQ1); Section *Correlates of Academic AI Use (RQ3)* examines how general perceptions relate to academic uses of AI (RQ3); Section *Regression Analyses (RQ5–RQ6)* reports the regression models predicting ethical concern and functional use (RQ5–RQ6); Section *Demographic Differences (RQ4, RQ7)* reports demographic differences (RQ4, RQ7); and Sections *Profiles of AI Users: Cluster Analysis* and *Path Analysis* present the cluster and path analyses, which integrate the preceding findings. The demographic composition of the sample has already been presented in Section *Participants and Sampling* (**Table 1**).

General AI Use and Perceptions (RQ2)

As shown in **Table 2**, students reported moderate usage frequency (M = 2.81, SD = 1.08) and slightly above-average familiarity with AI tools (M = 3.11, SD = 1.03). Self-reported familiarity, slightly above the midpoint, suggests broad awareness but considerable individual variation. Perceived reliability of AI-generated information was neutral (M = 3.00, SD = 0.79), indicating neither high trust nor pronounced distrust, with relatively little dispersion. By contrast, perceived ethical acceptability of using AI in academic work was lower (M = 2.60, SD = 1.01), highlighting reservations and ambivalence about whether AI use is ethically appropriate in higher education. Overall, the profile is one of engaged but cautious users who recognise AI's presence in academic work while remaining unsure about its ethical implications.

Table 3. Internal consistency (Cronbach's alpha) for Scales A–E

Scale	Description	Cronbach's α
A	Search for educational resources	0.895
B	Understanding of educational material	0.935
C	Solving problems in university studies	0.919
D	Cheating on exams and assignments	0.882
E	Ethical issues and regulation	0.828

Note. All coefficients indicate high internal consistency (α ⩾ .80).

Table 4. Descriptive statistics for Scales A–E (scale means and standard deviations)

Scale	Description	Mean	SD
A	Search for educational resources	2.96	0.83
B	Understanding of educational material	3.34	0.91
C	Solving problems in university studies	3.00	0.88
D	Cheating on exams and assignments	3.47	0.79
E	Ethical issues and regulation	3.69	0.61

Academic Uses of AI: Scale Properties and Levels (RQ1)

Principal component analyses yielded a single dominant factor for each of the five scales, supporting their unidimensionality. As shown in **Table 3**, internal consistency was high for every scale, with Cronbach's alpha ranging from 0.828 to 0.935. **Table 4** reports the mean scores and standard deviations for each scale, and **Table 5** presents the highest- and lowest-scoring items within each scale, illustrating which specific statements students endorsed most and least strongly.

Scale A (Search for educational resources; M = 2.96, SD = 0.83) indicates a moderately positive stance towards using AI to locate and access academic materials. Students particularly agreed that AI helps them find resources more quickly (e.g., "AI tools help me find academic resources faster than traditional methods", M = 3.46), while expressing less confidence in relying on AI to filter out low-quality sources or to identify reliable references. Scale B (Understanding of educational material; M = 3.34, SD = 0.91) shows that students generally view AI as a helpful tool for clarifying difficult concepts and simplifying complex content, with high means for items such as breaking down complex themes (M = 3.70), even if they do not always use AI systematically to create structured study guides. Scale C (Solving problems; M = 3.00, SD = 0.88) reflects moderate use of AI for problem-solving and idea generation: students tend to use AI to generate ideas and explore different approaches, but rely on it less for highly technical or mathematical tasks.

Scale D (Cheating on exams and assignments; M = 3.47, SD = 0.79) reveals strong agreement that AI tools make plagiarism and other forms of cheating easier. Students expressed high concern that AI could be used to copy, cheat in exams, or bypass academic integrity policies, while relatively few reported feeling direct pressure to engage in such misconduct. Scale E (Ethical issues and regulation; M = 3.69, SD = 0.61) recorded the highest mean, indicating broad support for ethical safeguards. Students strongly endorsed statements that AI tools should document their sources and that students should be educated about the ethical implications of AI, and they supported regulation of AI use in academia to ensure fairness, while expressing somewhat lower—but still positive—concern about data privacy and environmental

Table 5. Highest- and lowest-scoring items within each scale

Scale	Highest-scoring statements	M	Lowest-scoring statements	M
A	AI tools help me find academic resources faster than traditional methods	3.46	I rely on AI tools to compose high-quality educational resources	2.68
	AI tools make it easier to access a variety of educational journals and articles	3.42	I use AI tools to identify reliable sources for my research projects	2.66
	AI tools reduce the time I spend searching for reliable educational materials	3.20	I rely on AI tools to filter out irrelevant or low-quality sources	2.60
B	AI tools help me understand complex themes by breaking them down into simple words	3.70	I use AI tools to create study guides and summaries for my courses	2.87
	AI tools provide clarifications that enhance understanding of difficult concepts	3.70	AI tools make it easier to review and modify large amounts of study material	3.09
	AI tools help me retain information by providing brief summaries	3.44	AI tools improve my ability to understand the main ideas of the study material	3.25
C	AI tools help me generate ideas for projects and research	3.16	I use AI tools to explore possible scenarios or experiments to find better solutions	2.82
	I use AI tools to discover different approaches to solving problems	3.12	I rely on AI tools to process and solve complex problems	2.88
	AI tools improve my ability to handle challenging research tasks	3.09	I use AI tools to solve technical or mathematical problems in my research	2.88
D	I believe that AI tools should always document the basic sources of information they use	4.19	I feel pressure to use AI tools in an unethical way to keep up with my peers	2.37
	I believe that the use of AI tools makes plagiarism and copying easier	3.93	I believe that AI tools can eliminate inequalities in access to education	3.06
	I believe that AI tools will be used for cheating in exams or assignments	3.69	I believe that using AI tools to complete assignments reduces the value of education	3.26
	I am worried that AI tools make cheating more common among students	3.67	AI tools make it easy to bypass academic integrity and ethics policies	3.41
E	I believe that students should be educated about the ethical implications of using AI tools	4.06	I am concerned about the environmental impact of the development and use of AI tools	3.21
	I believe that AI use in academia should be regulated to ensure equity and fairness	3.89	I am concerned about the privacy of my data when using AI tools for academic purposes	3.38

Note. M = mean item score on a five-point scale. Item wording is presented in abbreviated form

Table 6. Spearman correlations (ρ) between general AI perceptions and Scales A–E

Perception item	Scale A	Scale B	Scale C	Scale D	Scale E
Frequency of AI use	.403**	.470**	.385**	−.148**	—
Familiarity	.281**	.331**	.301**	−.116*	−.113*
Perceived reliability	.397**	.402**	.370**	−.079	−.104*
Perceived ethical acceptability	.340**	.333**	.319**	−.337**	−.213**

Note. Spearman's ρ. ** p < .01; * p < .05. Coefficients shown without an asterisk are non-significant. Each item's redundant self-correlation (ρ = 1.000) has been omitted for clarity. Frequency of AI use was examined in relation to Scales A–D; the dash (—) denotes a coefficient not reported in the original analysis.

impact. Taken together, these results suggest that students recognise the educational utility of AI for understanding and problem-solving, but are simultaneously alert to risks of academic misconduct and strongly favour institutional guidance and regulation.

Correlates of Academic AI Use (RQ3)

Spearman's rho correlations were computed to explore the associations between the four general AI items (frequency of use, familiarity, perceived reliability, and perceived ethical acceptability) and Scales A–E. The coefficients and significance levels are presented in **Table 6**. To improve readability, the table reports, for each perception item, its correlation with each of the five scales; the redundant self-correlation of each item with itself (which necessarily equals 1.000) has been omitted, and statistical significance is indicated by asterisks defined in the table note.

Frequency of AI use was positively associated with Scales A–C (ρ = .385 to .470, $p < .001$), indicating that students who use AI more often rely on it more for information retrieval, comprehension support, and problem-solving. Its negative correlation with Scale D ($\rho = -.148$, $p = .002$) suggests that frequent users report somewhat fewer concerns about AI-facilitated cheating, possibly reflecting habituation. Familiarity showed positive correlations with Scales A–C (ρ = .281 to .331, $p < .001$) and small negative correlations with Scales D ($\rho = -.116$, $p = .014$) and E ($\rho = -.113$, $p = .018$). Perceived reliability correlated positively with Scales A–C (ρ = .370 to .402, $p < .001$) and weakly negatively with Scale E ($\rho = -.104$, $p = .028$), while its association with Scale D was not significant ($\rho = -.079$, $p = .095$). Finally, perceived ethical acceptability was positively associated with Scales A–C (ρ = .319 to .340, $p < .001$) and negatively with Scale D ($\rho = -.337$, $p < .001$) and Scale E ($\rho = -.213$, $p < .001$). Overall, more frequent, familiar, and trusting users report more extensive academic use of AI and somewhat lower levels of ethical concern and regulatory support.

Regression Analyses (RQ5–RQ6)

Several multiple linear regression models were estimated. In a model predicting Scale D (cheating and misconduct concerns) from Scales A–C and E, the overall regression was significant ($p < .001$) and explained 14.2% of the variance ($R^2 = .142$), with Scale E (ethical safeguards and regulation) the strongest predictor. Given the conceptual proximity between Scales D and E and the cross-sectional nature of the data, this finding is interpreted as an attitudinal association rather than a causal effect. Additional models examined the prediction of functional uses of AI. A model predicting Scale A from the remaining scales was significant ($R^2 = .299$, $p < .001$): higher scores on Scales B, D, and E were associated with greater use

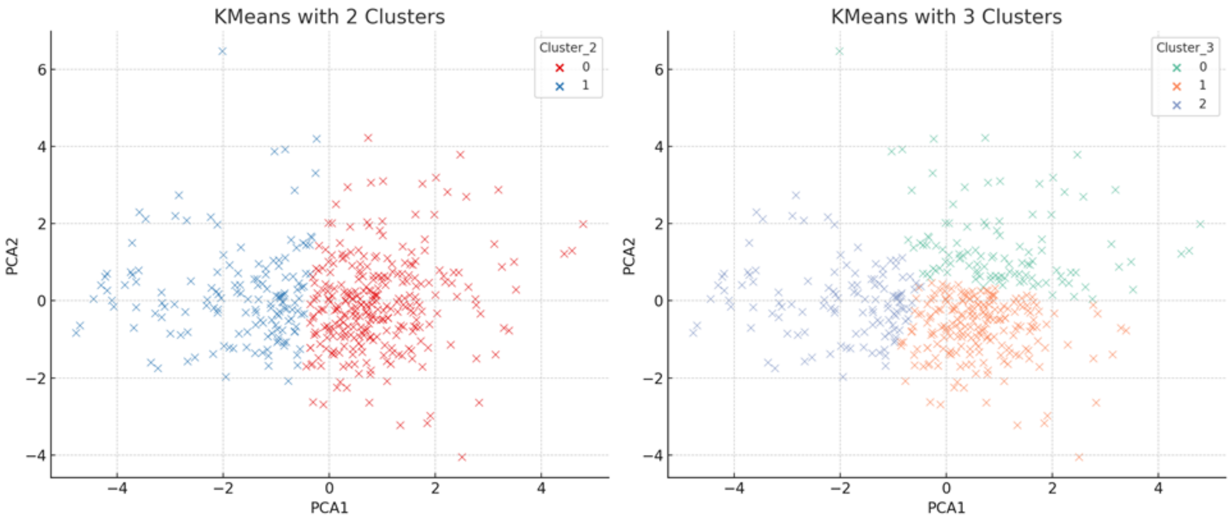

Figure 1. K-means cluster solutions for the two- and three-cluster models (projected onto the first two principal components) (Source: Authors' own elaboration)

Table 7. Cluster means for the two-cluster solution

Cluster (profile)	A	B	C	D	E
0 – Higher-engagement users	3.37	3.81	3.45	3.32	3.58
1 – Lower-engagement, higher-concern users	2.20	2.45	2.15	3.74	3.88

Note. A = Search for educational resources; B = Understanding of educational material; C = Solving problems; D = Cheating concerns; E = Ethical issues and regulation. Cluster labels (0, 1) are arbitrary algorithmic identifiers without ordinal meaning; profiles are named on the basis of the mean pattern.

of AI for locating academic resources (B: β = 0.196, $p < .001$; D: β = 0.292, $p < .001$; E: β = 0.138, $p < .001$). The strongest model predicted Scale B (comprehension) and accounted for 32.8% of its variance ($R^2 = .328$, $p < .001$), with significant predictors including Scales A (β = 0.268, $p < .001$), D (β = 0.286, $p < .001$), and E (β = 0.110, p = .005). These analyses should be viewed as exploratory mappings of associations within a multifaceted attitudinal space rather than as evidence of directional causal effects.

Demographic Differences (RQ4, RQ7)

An independent-samples Welch's t-test examined gender differences across Scales A–E. Women scored significantly higher than men on Scale D (cheating and misconduct concerns) and on Scale E (ethical issues and regulation), indicating higher ethical vigilance and stronger support for safeguards among female students, whereas no significant gender differences emerged for Scales A–C. A series of one-way ANOVAs tested for differences across age groups, field of study, parental education, residence, and perceived family financial situation. None of these comparisons reached statistical significance, indicating that, within this sample, AI-related attitudes and practices were relatively similar across these categories. This pattern is examined further, in relation to user profiles, in Section *Profiles of AI users: cluster analysis* (**Table 9**).

Profiles of AI Users: Cluster Analysis

K-means clustering was applied to the five scale scores to identify distinct profiles of AI users. Silhouette scores for solutions with two to nine clusters indicated that the two- and three-cluster solutions provided the best balance between cohesion and separation (**Figure 1**).

In the two-cluster solution (**Table 7**), the two profiles can be characterised as follows. Cluster 0 comprises higher-engagement users: students with comparatively higher use of AI across Scales A–C and lower scores on cheating concerns (Scale D). Cluster 1 comprises lower-engagement, higher-concern users: students with lower functional use and higher concern about cheating and ethical issues. The cluster labels (0 and 1) are arbitrary identifiers assigned by the algorithm and carry no ordinal meaning; their substantive interpretation is given by the mean profiles in **Table 7**.

The three-cluster solution (**Table 8**) offered a more nuanced differentiation, with three distinct profiles. Cluster 0 (balanced users) shows moderate-to-high use of AI for resources, understanding, and problem-solving, combined with comparatively lower cheating concern and regulatory support. Cluster 1 (heavy adopters) shows high scores across Scales A–C together with high agreement on AI-related cheating and ethical risk and strong support for ethical safeguards. Cluster 2 (low-engagement users) shows low scores on functional AI use and high scores on cheating concerns and ethical safeguards, indicating limited reliance on AI coupled with pronounced ethical reservations.

Chi-square and ANOVA tests were conducted to examine associations between cluster membership and demographic variables. As shown in **Table 9**, only gender is significantly associated with cluster membership (p = .006), while no significant differences are observed for age, field of study, area of residence, family financial situation, or parental education.

Path Analysis

Finally, an exploratory path model was estimated to capture potential pathways linking different types of AI use to cheating concerns and ethical attitudes. The model specified

Table 8. Cluster means for the three-cluster solution

Cluster (profile)	A	B	C	D	E
0 – Balanced users (lower concern)	3.13	3.60	3.28	2.53	2.96
1 – Heavy adopters (higher concern)	3.39	3.79	3.40	3.72	3.88
2 – Low-engagement users	2.09	2.35	2.08	3.87	3.99

Note. Scale codes A–E as defined for Table 7. Cluster labels (0, 1, 2) are arbitrary algorithmic identifiers without ordinal meaning.

Table 9. Association between cluster membership and demographic variables

Demographic variable	Test	p
Age	One-way ANOVA	0.782
Gender	**Chi-square**	**0.006**
Area of residence	Chi-square	0.436
Field of studies	Chi-square	0.459
Family financial situation	Chi-square	0.428
Father's education	Chi-square	0.473
Mother's education	Chi-square	0.189

Note. Only gender is significantly associated with cluster membership ($p < .01$); all other associations are non-significant.

two main trajectories. The first is a constructive path from AI-assisted resource search to comprehension and then to problem-solving: A → B (β = 0.69), B → C (β = 0.53), and a direct A → C link (β = 0.33), indicating that some students move directly from accessing resources to solving tasks with AI support. The second is a shortcut/risk path linking comprehension and cheating concerns to ethical attitudes: B → D (β = −0.18), suggesting that deeper engagement with AI for learning is associated with slightly lower agreement that AI facilitates cheating; D → E (β = 0.65), indicating that awareness of cheating risks coexists with heightened ethical sensitivity and support for safeguards; and C → E (β = −0.02), indicating that problem-solving with AI has no meaningful direct association with ethical attitudes. This model highlights the dual nature of AI in students' academic lives: AI can support a constructive trajectory of enhanced access, understanding, and problem-solving, while simultaneously raising concerns about cheating that feed into demands for ethical guidance and regulation. Given the cross-sectional design and the use of observed scale scores, the path analysis is interpreted heuristically, as a structured visualisation of the pattern of associations rather than as a test of causal mechanisms.

DISCUSSION

Summary of Main Findings

The present study set out to examine how students in Greek public universities engage with generative AI for academic purposes and how this engagement relates to perceptions of reliability, ethical acceptability, concerns about misconduct, and support for regulation. The findings can be summarised in relation to the research questions. With respect to the extent of academic use (RQ1), students reported moderate but meaningful use of AI for searching educational resources (Scale A), understanding material (Scale B), and solving problems (Scale C), with comprehension support being the most strongly endorsed function. Regarding perceptions of reliability and ethical acceptability (RQ2), students were neutral about the reliability of AI-generated information and comparatively reserved about its ethical acceptability. The correlational analyses (RQ3) showed that more frequent, familiar, and trusting users relied more heavily on AI for academic tasks. The regression and difference analyses (RQ4–RQ6) indicated that ethical attitudes and functional use were intertwined and that women expressed stronger ethical concern (Scale D) and support for regulation (Scale E). Finally, with respect to demographic differences in ethical orientation (RQ7), gender was the only background variable significantly associated with both ethical concern and user profile membership.

Generative AI as Cognitive Scaffold and Potential Shortcut

The results reaffirm the double-edged character of generative AI in academic life. On the one hand, students use AI as a cognitive scaffold: a resource that helps them access materials, decompose complex ideas, and generate approaches to problems. This is consistent with constructivist accounts in which meaning is actively built through mediated activity (Bruner, 1990), and it resonates with the framing of AI as a tool that can extend learners' capabilities when used deliberately (Luckin et al., 2016). The prominence of comprehension support (Scale B) suggests that, for many students, AI functions less as a means of avoiding intellectual work than as a means of making demanding material more tractable.

On the other hand, the same affordances can serve as a shortcut that bypasses the effortful processes through which durable learning occurs, and students themselves recognise this risk: agreement was high that AI makes plagiarism and cheating easier (Scale D). The coexistence of extensive use with strong ethical concern is theoretically interesting. Rather than eroding ethical awareness, more intensive engagement with AI appears to coincide with a clear-eyed recognition of its risks. This pattern can be read through the lens of moral disengagement (Bandura, 1999): the fact that students who find AI more ethically acceptable report fewer cheating concerns suggests that the normalisation of AI use may, for some, attenuate the salience of integrity violations. The negative association between perceived ethical acceptability and concern about misconduct, observed in the present study, is consistent with this interpretation and underscores that perceptions of acceptability are themselves an important target for educational intervention.

A Sociotechnical Reading

Interpreted through Feenberg's critical theory of technology (Feenberg, 1995, 2002, 2017), these findings indicate that students do not experience AI as a neutral instrument but as a contested sociotechnical system. Their strong support for transparency and regulation (Scale E, the highest-scoring scale) can be understood as a demand for the democratic governance of a technology whose design and institutional deployment they do not fully control. The heterogeneity revealed by the cluster analysis—ranging from heavy adopters with high ethical sensitivity to low-engagement users with pronounced reservations—further suggests that there is no single "student stance" towards AI, but rather a plurality of positions shaped by experience and disposition. This plurality is precisely what a sociotechnical perspective would predict, and it cautions against one-size-fits-all institutional responses.

Towards Human-, Student-, and Educator-Centred Generative AI

The finding that students simultaneously value AI and call for its regulation points towards the need for human-centred approaches to generative AI in higher education—approaches that place the development, agency, and wellbeing of learners and educators at the centre of design and policy. International frameworks have begun to articulate what such an orientation entails. UNESCO's competency frameworks for teachers and for students foreground a human-centred mindset, ethical and critical engagement, and the responsible co-existence of human and machine agency as core competencies for the AI era (UNESCO, 2024a, 2024b). A student-centred orientation implies cultivating AI literacy that enables learners to use these tools critically and transparently rather than merely efficiently, while an educator-centred orientation implies equipping teachers with the competencies needed to design learning experiences in which AI supports, rather than supplants, higher-order thinking.

Recent scholarship makes the educator dimension concrete: GenAI-responsive competency frameworks argue that the integration of generative AI requires moving teacher competence beyond technical proficiency to encompass pedagogical strategies that foster critical, ethical, and developmentally appropriate student–AI collaboration (Sun et al., 2026). This converges with calls to take teacher education seriously as a site of AI preparation (Salas-Pilco et al., 2022) and with proposals for a social and ethically grounded conception of generative AI for education (Sharples, 2023). At the policy level, the European Commission's ethical guidelines for educators on the use of AI and data in teaching and learning (European Commission, 2022) and broader frameworks for national AI-in-education strategy (Schiff, 2022) provide scaffolding for translating a human-centred orientation into institutional practice. The present findings—strong student demand for transparency, source documentation, and education about AI ethics—are best served by precisely such human-, student-, and educator-centred frameworks, rather than by reactive prohibition.

Educational and Policy Implications

Several implications follow. First, the strong endorsement of ethical safeguards suggests that institutions should move from prohibition towards clear, positive guidance on acceptable AI use, complemented by explicit instruction in AI literacy and academic integrity. This aligns with European competence frameworks that position digital and critical competencies as central to lifelong learning (Council of the European Union, 2018) and with principles for trustworthy AI (European Commission, 2019). Second, because students perceive AI as a facilitator of misconduct, assessment practices may need to be redesigned so that they remain valid in an environment of widely available generative tools—for example, by emphasising process, reflection, and authentic tasks rather than easily automatable products (Gardner et al., 2021; Stokel-Walker, 2022; Swiecki et al., 2022). The scale of student adoption documented internationally (Digital Education Council, 2024) makes such redesign increasingly urgent. Third, the heterogeneity of user profiles implies that interventions should be differentiated: heavy adopters may benefit most from guidance on responsible and transparent use, whereas low-engagement, high-concern students may benefit from support that builds confidence and critical competence. Finally, the persistent unevenness of the evidence base—reflected in successive systematic reviews of AI in higher education (Lai & Bower, 2020; Sarwari, 2025; Ullrich et al., 2022)—reinforces the need for context-sensitive, theoretically informed research of the kind attempted here.

CONCLUSION

This study examined how undergraduate students in Greek public universities engage with generative AI for academic purposes and how this engagement relates to their perceptions of reliability, ethical acceptability, concerns about misconduct, and support for regulation. All of the research aims set out in Section *Research aims and questions* were addressed. The study established the extent and the principal functions of students' academic AI use (RQ1) and characterised their perceptions of reliability and ethical acceptability (RQ2); it mapped the associations between general perceptions and academic uses of AI (RQ3); it estimated the factors associated with functional use, ethical concern, and support for regulation (RQ4–RQ6); and it identified the demographic correlates of ethical orientation, with gender emerging as the single significant background factor (RQ7). In doing so, the study delivered its intended outcomes: a validated, original measurement instrument; an empirically grounded account of AI engagement in an under-researched national context; and a typology of student user profiles.

The principal contribution of the study is threefold. Empirically, it provides one of the first systematic, quantitative accounts of student engagement with generative AI in Greek higher education, addressing a documented gap in evidence from non-Anglophone European systems. Methodologically, it contributes an original, content-validated instrument with high internal consistency for assessing AI-related academic practices and attitudes. Theoretically, it demonstrates the value of a sociotechnical reading of student–AI relations, showing that intensive use and strong ethical concern coexist rather than trade off. The central practical message is that students are neither uncritical adopters nor opponents of AI: they use it pragmatically while demanding transparency, education, and regulation—demands that institutions are well placed to meet through human-, student-, and educator-centred policies.

Limitations

Several limitations should be borne in mind when interpreting these findings. First, the study employed a non-probability convenience sample, complemented by snowball recruitment, which limits the statistical generalisability of the results to the wider Greek student population. Second, the sample was markedly imbalanced with respect to gender, with women comprising 83.5% of respondents, and was dominated by students from the humanities and social sciences. The observed gender differences (on Scales D and E) should therefore be regarded as preliminary and interpreted with caution, since the small male subsample limits the precision and representativeness of between-gender comparisons. Third, the cross-sectional design precludes causal inference; the regression and path analyses describe patterns of association at a single point in time and should not be read as evidence of directional effects. Fourth, all measures were based on self-report and may be subject to social desirability and recall biases, particularly for sensitive items concerning academic misconduct. Fifth, although the instrument was developed through a structured two-phase validation process and a pilot administration, it is a newly constructed measure, and principal component analysis was used for the preliminary examination of its structure; further psychometric work, including confirmatory factor analysis on independent samples, would strengthen confidence in the scales.

Directions for Future Research

These limitations point to several avenues for future research. Subsequent studies should employ probability-based or stratified sampling and seek more balanced representation across gender and academic disciplines, so that demographic differences can be estimated with greater precision and generalised more confidently. Longitudinal designs would allow researchers to trace how patterns of AI use and ethical orientation evolve as tools, norms, and institutional policies change. Mixed-methods and qualitative approaches could illuminate the meanings students attach to AI use and the reasoning behind their ethical positions, complementing the quantitative patterns reported here. Cross-national comparative work would help to distinguish features specific to the Greek context from more general dynamics, and the incorporation of behavioural or trace data, alongside self-report, would mitigate common-method concerns. Pursuing these directions would deepen understanding of how generative AI can be integrated into higher education in ways that support learning while safeguarding academic integrity.

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AI statement: The authors stated that, during the preparation of this manuscript, they used Claude (Anthropic) solely for language editing and to improve the clarity of expression. The tool was not used to generate data, conduct analyses, produce figures, or formulate the study's arguments or conclusions. After using this tool, the authors reviewed and edited the text as necessary and take full responsibility for the content of the publication.

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Data protection (GDPR): Data processing complied with the General Data Protection Regulation (EU) 2016/679. Data minimization principles were applied and no direct identifiers were collected. The dataset was stored in access-controlled files at the Laboratory of Sociology and History of Education, Department of Philosophy, University of Ioannina (Greece). Access was restricted to the research team. Only aggregated results are reported to minimize any risk of re-identification. The data will be retained for a minimum of three (3) years and then securely deleted.

Availability of data and materials: The anonymized dataset and analysis code are available from the corresponding author upon reasonable request.

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