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Profiling University Students' Academic AI Use Through Correspondence Analysis Across Disciplines

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Abstract

Generative artificial intelligence (AI) is rapidly reshaping higher education, not only as a technological tool but as a mediator of how students engage with knowledge, academic tasks, and cognitive processes. However, students do not appear to adopt AI in uniform ways, and existing research has largely overlooked how patterns of use are structured across disciplines and academic contexts. Drawing on the Technology Acceptance Model, digital inequality research, and scholarship on disciplinary cultures, this study profiles academic AI use among 826 university students using Correspondence Analysis (CA).

Participants completed a categorical survey capturing frequency of use, perceived usefulness, confidence, time investment, recency, supported academic tasks, platforms used, and demographic and academic characteristics. The first two CA dimensions accounted for 81.42% of total inertia. Dimension 1 (72.56%) represented a continuum from intensive, high-confidence, technically oriented engagement to occasional, supportive use, while Dimension 2 (8.86%) differentiated patterns by recency of AI use. Three dominant profiles emerged, A technical–productive profile, an academic-support profile and finally a Low-Use

The findings suggest that academic AI use is not a uniform behaviour but a structured and discipline-sensitive configuration shaped by perceived utility, confidence, recency, and epistemic context. More broadly, the study contributes to a reconceptualisation of AI in higher education as a socio-cognitive infrastructure, highlighting the need for differentiated AI literacy, discipline-aligned pedagogical design, and equitable integration strategies.

Introduction

Generative artificial intelligence (GenAI) has moved from a peripheral technological innovation to an everyday academic resource in higher education. Large language models and related AI tools are now used for idea generation, drafting, coding, feedback, information retrieval, translation, and study support. At the same time, their adoption has raised substantial pedagogical and ethical questions concerning overreliance, accuracy, academic integrity, and the reconfiguration of students' cognitive work (Dwivedi et al., 2023; Meyer et al., 2023). As implementation activity accelerates, higher education institutions are increasingly expected to balance innovation with responsible use, equitable access, and coherent policy development (Belkina et al., 2025).

The wider artificial intelligence in education (AIEd) literature shows that AI is already implicated in diverse educational functions, including intelligent tutoring, personalised support, adaptive learning, predictive analytics, assessment, and feedback. Systematic reviews confirm a sharp expansion of AI-related educational research, especially since 2022, while also noting considerable heterogeneity in educational goals, settings, and methodological approaches (Chiu et al., 2023; Wang et al., 2024). Research on explainable AI and AI-based feedback further suggests that students' interactions with such

systems are shaped not only by technical capability but also by the interpretability, usefulness, and contextual fit of the tools themselves (Khosravi et al., 2022; Yildiz D., & Onan, 2025).

Despite this rapid growth, the empirical picture of students' day-to-day academic AI use remains fragmented. Much of the existing literature focuses on a single platform, most often ChatGPT, or on a narrow subset of educational activities, such as academic writing or language learning (Albadarin et al., 2024; Nelson et al., 2025). In addition, earlier reviews of AIEd in higher education pointed to the limited participation of educators and educational researchers in framing the pedagogical implications of AI use, leaving substantial questions about how students actually embed AI in discipline-specific academic practice (Zawacki-Richter et al., 2019). As a result, there is still limited evidence on how AI use patterns vary across academic disciplines, levels of study, and institutional contexts, particularly when students' behaviour is examined as a configuration of tasks, platforms, confidence, and perceived value rather than as isolated variables.

Recent empirical studies further confirm that students' engagement with generative AI is shaped by task demands, assessment structures, and perceptions of academic risk and legitimacy. For instance, research shows that students tend to use AI more frequently for low-stakes or preparatory tasks, such as brainstorming and summarisation, while remaining more cautious in high-stakes assessment contexts (Wang et al., 2023; Cotton et al., 2024). At the same time, emerging evidence suggests that students' AI practices are strongly influenced by institutional guidance and clarity around acceptable use, with ambiguous policies often leading to either overreliance or complete avoidance (Kasneci et al., 2023; Rudolph et al., 2023).

A growing body of research also highlights the role of motivational, demographic, and institutional factors in shaping academic engagement, performance, and well-being in higher education (Vlachopanou et al., 2026; Vlachopanou et al., 2025; Kalamaras et al., 2025).

A growing body of work also highlights the role of self-regulated learning in shaping AI use, indicating that students who demonstrate higher metacognitive awareness are more likely to use AI tools strategically rather than passively. In parallel, concerns have been raised regarding the potential impact of AI on cognitive offloading and reduced deep learning when tools are used without critical engagement. Furthermore, cross-national studies suggest that patterns of AI adoption may vary depending on educational culture, digital infrastructure, and prior exposure to educational technologies (UNESCO, 2023; OECD, 2024).

Taken together, these findings reinforce the need to move beyond generalised accounts of AI adoption and toward more fine-grained analyses that capture how students integrate AI into discipline-specific academic practices.

The present study is theoretically informed by the Technology Acceptance Model (TAM) and its extensions. TAM proposes that individuals' intentions to adopt technology are shaped primarily by perceived usefulness and perceived ease of use (Davis, 1989), while later work expanded the framework

to include the role of social influence, output quality, and job, or task, relevance (Venkatesh & Davis, 2000). In educational settings, these constructs remain highly relevant because students' use of AI tools is not determined solely by availability; rather, it depends on whether students believe the tools are helpful, manageable, trustworthy, and appropriate for the tasks they need to complete. When students perceive AI to be useful and feel confident in their ability to use it, higher-frequency and more sophisticated patterns of engagement become more likely. Recent work has further operationalised AI-related motivation and basic psychological needs through validated measurement frameworks, providing evidence that students' engagement with AI is closely linked to motivational and need-based processes (Maska, 2026, Maska et al., 2026; Maska et al., 2025).

A second theoretical lens concerns digital inequality and digital readiness. Even when tools are widely available, students differ in the skills, confidence, and prior exposure needed to convert access into meaningful educational use. Research on digital readiness shows that disparities in digital skills can shape the extent to which learners benefit from new technologies and can contribute to uneven educational outcomes (van de Werfhorst et al., 2022). In the context of AI, these differences are likely to manifest as variation in confidence, experimentation, recency of use, and task complexity. Students who remain current with rapidly evolving AI tools may be better positioned to benefit from improved interfaces and expanding functionalities, whereas students with limited exposure or lower digital confidence may confine AI use to peripheral or supportive tasks.

A third lens comes from scholarship on disciplinary cultures. Academic disciplines are not neutral settings; they organise forms of knowledge, preferred methods, legitimate tools, and conceptions of rigour in different ways. Becher and Trowler (2001) argued that disciplines can be understood as "tribes" with distinctive epistemic cultures and working practices. Applying this insight to AI adoption suggests that students in fields where computational reasoning, technical problem solving, or productivity-oriented workflows are central may be more inclined to use AI intensively and instrumentally. By contrast, students in fields with stronger interpretive, relational, or profession-based traditions may integrate AI more cautiously, selectively, or supportively. Recent AI-in-education reviews imply such disciplinary differentiation, but few empirical studies have mapped it directly across multiple academic fields (Wang et al., 2024).

Against this background, the present study examines academic AI use among university students through Correspondence Analysis (CA), a multivariate technique designed for the exploration of high-dimensional categorical data (Greenacre, 2017). Rather than estimating one predictor at a time, CA makes it possible to visualise how categories of use cluster together in a shared geometric space. This is particularly appropriate for the present dataset, which contains categorical indicators of usage frequency, confidence, perceived usefulness, recency, time investment, platforms, tasks, and student characteristics. The approach therefore allows us to move beyond average differences and toward a relational profile of academic AI behaviour.

Purpose of the Present Study and Hypotheses

The purpose of the present study was to identify distinct profiles of academic AI use among university students and to examine how these profiles relate to discipline, level of study, gender, and institutional context. By using Correspondence Analysis, the study sought to map the structure of associations among categories of AI use and demographic or academic variables without imposing a priori linear assumptions. In doing so, the study aimed to provide a discipline-sensitive account of AI adoption in higher education and to generate evidence that can inform curricular design, AI literacy initiatives, and institutional support strategies.

On the basis of the literature reviewed above, four hypotheses guided the analysis.

First, we expected that AI use would vary across academic disciplines, with students in Computer Science and business-related or quantitatively oriented fields showing higher-engagement profiles than students in Humanities, Psychology, and Health-related areas. **Second**, we expected higher-frequency use to co-occur with greater perceived usefulness and confidence, consistent with TAM and related acceptance models.

Third, we expected recency of use to operate as a meaningful dimension of variation, with more recent users displaying stronger engagement patterns than students whose interaction with AI had lapsed.

Fourth, we expected the categories to form coherent behavioural clusters rather than random combinations, reflecting the joint influence of technological perceptions, digital readiness, and disciplinary culture.

Method

Ethics

The study protocol (approval code OR-25-AOC-2702) was reviewed and approved by the PGR AOC Research Ethics Committee of Aegean College, chaired by Academic Director & Chair of Research Committee, Dr. Grigoris Risvas, on February 27, 2025. The research was conducted in accordance with the Committee's ethical guidelines and the principles of the Declaration of Helsinki, ensuring voluntary participation, anonymity, informed consent for both participation and publication, and the protection of participants' rights and well-being throughout the study. Note that the manuscript contains no identifiable personal data or images.

Participants

From an initial sample of 924 students, 18 participants who did not wish to report their gender were excluded, along with 16 participants who reported that they did not use any AI tools for academic purposes. The final valid sample comprised 826 university students. Women represented 73.4% of the sample and men 26.6%; 65.5% were enrolled in undergraduate programmes and 34.5% in postgraduate programmes. Students came from Computer Science (8.1%), positive/business disciplines (22.5%),

Humanities, Social & Education Sciences (22.4%), Psychology (22.6%), Health & Biology (21.3%), and other natural sciences (3.0%). Participants represented both public (21.3%) and private (78.7%) higher education institutions. Participation was voluntary and anonymous, and no identifying information was collected.

Table 1
Sample Characteristics

Characteristic	**n**	**%**
Gender		
Male	220	26.6
Female	606	73.4
Level of study		
Undergraduate	541	65.5
Postgraduate	285	34.5
Academic field		
Computer Science	67	8.1
Positive/Business disciplines	186	22.5
Humanities, Social & Education Sciences	185	22.4
Psychology	187	22.6
Health & Biology	176	21.3
Other Natural Sciences	25	3.0
Institutional sector		
Public	176	21.3
Private	650	78.7

Note. Counts are rounded from the percentages reported in the source dataset (N = 826) and sum to the final valid sample.

Instrument

Data were collected between August 2025 and February 2026 using a structured online questionnaire designed to capture patterns of AI use in academic contexts. The instrument comprised categorical variables measuring frequency of use (e.g., very often, sometimes/rarely), perceived usefulness, confidence, time spent using AI tools, recency of use, AI platforms employed (e.g., ChatGPT, Claude, Gemini, Perplexity, GrammarlyGO, Copilot), and the types of academic tasks for which AI was used (e.g.,

coding, summarising, generating text, grammar checking, exam preparation, and peer/tutor simulation). Additional items captured demographic and academic information, including gender, level of study, discipline, and type of institution. The questionnaire was pilot tested for clarity before administration.

Procedure

Participants completed the questionnaire electronically via a survey platform after being informed about the purpose of the study and the anonymous nature of participation. Completion implied informed consent. Responses were screened for completeness and eligibility before analysis. Because the analytic aim was to capture relationships among categories rather than estimate latent scale scores, only valid categorical responses were retained for the final Correspondence Analysis.

Data Analysis

Correspondence Analysis (CA) was used to examine the associations among categories of AI use and demographic or academic characteristics. CA is particularly suitable for the analysis of multiway categorical data because it decomposes the chi-square association structure of contingency tables into orthogonal dimensions that can be interpreted visually and substantively (Greenacre, 2017). The analysis was performed on a Burt matrix. Dimensional interpretation was based on the proportion of explained inertia, the relative position of categories in the factorial map, and the coherence of emergent clusters across tasks, platforms, and student characteristics. Because CA is exploratory, emphasis was placed on configuration, proximity, and conceptual structure rather than on directional causal inference. The clustering process was based on AI usage characteristics projected onto the axes derived from Correspondence Analysis, which represented key grouping variables (gender, educational level, and academic field). Each characteristic was assigned to a cluster using a classifier that evaluated its Euclidean distance from these groups. Three distinct profiles emerged (as described below), reflecting coherent patterns across user behaviours, demographic characteristics, and preferred platforms.

Results

Dimensional Structure

The Correspondence Analysis yielded a two-dimensional solution that accounted for 81.42% of the total inertia.

Dimension 1 explained 72.56% of the variance and represented a continuum from intensive, high-engagement AI use to occasional or low-engagement patterns. Categories such as very often, very or extremely useful, completely confident, and extended usage durations (e.g., more than 10 hours) were located on the high-engagement side of the map. These categories were closely associated with technically and productively oriented academic uses, including writing or debugging code, solving mathematical or logical problems, generating academic text, translating content, and summarising texts. By contrast, sometimes/rarely, not or slightly useful, not or slightly confident, and minimal time investment (e.g., less than one hour) clustered on the lower-engagement side, together with supportive

academic uses such as grammar checking, study note creation, exam preparation, and simulated peer or tutor interaction.

Dimension 2 accounted for a further 8.86% of the variance and primarily differentiated participants on the basis of recency of AI use. Categories such as within the past 3 months and 3–12 months ago were positioned opposite over a year ago, indicating that temporal proximity to AI use formed a secondary but conceptually meaningful axis of differentiation. This suggests that the recency with which students have interacted with AI is associated with qualitatively different patterns of confidence, perceived utility, and task selection.

Figure 1

Two-Dimensional Correspondence Analysis Map of AI Usage Categories and Demographic/Academic Groups

Note

Blue circles represent AI-use Characteristics ; orange triangles represent demographic and academic categories. Dimension 1 (72.56% of inertia) differentiates intensive, high-confidence, technically oriented AI use from occasional, low-engagement, and supportive academic use. Dimension 2 (8.86%) reflects recency of use.

Cluster Interpretation

Three coherent clusters were evident in the factorial space. The first was a technical–productive cluster comprising coding, debugging, problem solving, text generation, translation, and summarisation. This cluster was associated with male students, postgraduate status, private institutions, and fields such as Computer Science and positive/business disciplines. The second was an academic-support cluster, encompassing grammar checking, study notes, exam preparation, and peer/tutor simulation. This cluster aligned with female and undergraduate students, public institutions, and fields such as Humanities, Social & Education Sciences, Psychology, and Health & Biology. A third cluster reflected lower engagement, bringing together categories of low frequency, low perceived usefulness, low confidence, and more temporally distant use.

Table 2

Clusters of AI Usage Patterns

Cluster	AI Use Characteristics	Associated Groups	Platforms
Technical–Productive	Coding, debugging, problem solving, text generation, translation, summarisation	Male, postgraduate, private institutions, Computer Science, positive/business disciplines	ChatGPT, Claude, Gemini, Perplexity
Academic-Support	Grammar checking, study notes, exam preparation, peer/tutor simulation	Female, undergraduate, public institutions, Humanities, Psychology, Health	GrammarlyGO, Copilot, Other
Low-Use	Low frequency, low usefulness, low confidence, older use patterns	Mixed lower-engagement groups	Mixed

Note. Cluster labels were assigned interpretively on the basis of the spatial proximity of task, platform, confidence, usefulness, and demographic categories in the factorial map.

Based on the above mentioned clustership three dominant AI User profiles emerged. A technical–productive profile, encompassing coding, problem solving, text generation, translation, and summarisation, was associated with postgraduate status, private institutions, and students in Computer Science and quantitatively oriented fields. An academic-support profile, grammar checking, study note creation, exam preparation, and simulated peer or tutor interaction, was associated with undergraduate status, public institutions, and students in Humanities, Social Sciences, Psychology, and Health-related disciplines. Finally, a Low-Use profile which includes AI users who place limited value on the capabilities of AI and demonstrate low trust in its outcomes. These individuals tend to rely on simpler, more traditional usage patterns, engage only when a specific need arises, and represent a mixed, low-engagement group that has not integrated AI into daily routines.

Platform Patterns

Platform use mirrored the behavioural structure of the factorial solution. ChatGPT, Claude, Gemini, and Perplexity aligned with intensive and technically oriented engagement, suggesting that students who used AI more frequently were also more likely to diversify their platform repertoire beyond a single mainstream tool. By contrast, GrammarlyGO, Copilot, and the residual “other” category clustered with supportive or peripheral academic uses, indicating a more bounded or instrumental relationship with AI. The spatial correspondence between platforms and task clusters reinforces the interpretive coherence of the CA solution and suggests that platform choice is part of broader behavioural profiles rather than a purely separate preference.

Goodness-of-Fit

Goodness-of-fit statistics supported the adequacy of the Correspondence Analysis model. The chi-square test was statistically significant, $\chi^2(385) = 2357.17$, $p < .001$, indicating that the contingency structure departed substantially from independence. Total inertia was 0.016, and Cramér’s V was 0.038.

Although this effect size is modest, such values are not unusual in large, high-dimensional categorical tables, particularly when behaviour is distributed across many task, platform, and background categories. The steep drop in eigenvalues after the first dimension further supported a primary interpretive focus on the first two axes. Taken together, these indicators suggest that the model captured a meaningful, though necessarily exploratory, structure in the data.

Discussion

The present study set out to profile academic AI use across university disciplines and to interpret variation in use through the lenses of technology acceptance, digital inequality, and disciplinary culture. The results show that academic AI use is structured along a continuum rather than distributed randomly. The first and dominant dimension separated intensive, technically oriented, high-confidence use from occasional, low-confidence, supportive use. This pattern is closely aligned with the Technology Acceptance Model. Students who used AI more frequently also reported greater perceived usefulness and confidence, which is precisely the configuration TAM would predict when a technology is seen as effective for relevant tasks (Davis, 1989; Venkatesh & Davis, 2000). In this sense, adoption in the present sample appears to involve a reinforcing cycle in which usefulness and confidence travel together with more demanding academic applications.

The results also support the view that AI use is embedded within disciplinary cultures. Students in Computer Science and business-related or quantitatively oriented fields were located close to coding, debugging, problem solving, text generation, translation, and summarisation. These uses are consistent with curricula that normalise iterative experimentation, digital production, and tool-mediated efficiency. By contrast, students in Humanities, Social Sciences, Psychology, and Health-related disciplines were associated with supportive uses such as grammar checking, study notes, exam preparation, and peer/tutor simulation. From the perspective of disciplinary cultures, this difference is unsurprising: fields differ in what counts as legitimate academic work, how knowledge is produced, and how tools are incorporated into that process (Becher & Trowler, 2001). Recent syntheses of AIEd research have repeatedly called for more discipline-sensitive accounts of AI use, and the present findings help address that need by showing that task choice, platform preference, and confidence form recognisable disciplinary patterns rather than a single generic adoption curve (Wang et al., 2024; Zawacki-Richter et al., 2019).

A second contribution of the study is the identification of recency of AI use as an independent axis of variation. Students who had used AI within the previous three to twelve months were positioned differently from those whose use was more distant in time. This suggests that AI adoption is not only a matter of whether students have ever used these tools, but also of whether they remain current with rapidly evolving systems. Newer tools and newer versions of existing tools often offer improved usability, better multimodal functionality, and richer pedagogical affordances, which may strengthen both engagement and perceived usefulness (Belkina et al., 2025; Khosravi et al., 2022). Conversely, students

whose prior experiences were earlier or less sustained may retain impressions formed on less capable systems, which can dampen confidence and discourage experimentation with more complex tasks.

The findings further illuminate a digital inequality perspective on AI in higher education. The distinction between intensive and supportive users does not simply indicate preference; it likely also reflects uneven digital readiness, uneven familiarity with task-appropriate tools, and uneven capacity to translate access into academic advantage. Digital inequality research has shown that differences in digital skills and confidence remain consequential even when technologies are broadly available (van de Werfhorst et al., 2022). In the present study, lower-confidence and lower-frequency users tended to cluster around supportive uses, suggesting that many students may be operating at a surface level of AI engagement. If left unaddressed, such differences could reproduce academic inequalities, especially if more AI-literate students disproportionately benefit from time savings, productivity gains, and enhanced access to formative support. Complementary modelling approaches in higher education have also demonstrated that students' motivations, expectations, and preparation are associated with progression and time-to-degree outcomes (Kalamaras et al., 2025a, b).

The findings of the present study contribute to an emerging reconceptualisation of AI in higher education as a socio-cognitive infrastructure rather than a discrete technological tool. The distinction observed between technical–productive and academic-support profiles reflects not only differences in usage frequency but also deeper differences in how students integrate AI into their epistemic practices. In this sense, AI use can be understood as part of a broader ecology of learning, in which tools, disciplinary norms, and cognitive strategies interact dynamically (Holmes et al., 2019).

Importantly, the results highlight a potential stratification in AI engagement that aligns with concerns about digital inequality and uneven AI literacy development. Students positioned within intensive usage profiles appear to leverage AI as an extension of problem-solving and knowledge production, whereas others engage with AI primarily as a support mechanism for existing study practices. This distinction resonates with broader concerns regarding the uneven development of AI literacy across student populations (Long & Magerko, 2020) and reinforces the argument that access alone does not ensure meaningful or equitable use.

For higher education practice, the implications are therefore significant. Institutions should avoid treating AI literacy as a generic transversal competence that develops uniformly across programmes. Instead, support should be differentiated by discipline and aligned with the epistemic and assessment demands of specific fields. Students in high-adoption domains may benefit from structured guidance on critical evaluation, verification, transparency, and advanced AI workflows, whereas students in lower-adoption fields may require scaffolded opportunities to build confidence and understand legitimate and context-appropriate use cases.

At the same time, programme teams should carefully consider the relationship between AI use and assessment design. The prevalence of supportive uses in disciplines such as Humanities, Psychology, and Health suggests that many students are already integrating AI into routine study practices, even

when not engaging in production-oriented tasks. This challenges binary distinctions between “use” and “misuse” and calls for more nuanced assessment guidance that articulates acceptable forms of support, disclosure, and human oversight (Albadarin et al., 2024; Meyer et al., 2023; Rudolph et al., 2023; Liu et al.,2023).

These implications align with a growing body of literature emphasising the need for pedagogically grounded integration of AI. Without explicit instructional design and guidance, AI tools risk reinforcing surface-level learning strategies and amplifying existing inequalities in digital competence (Holmes et al., 2019). Conversely, when embedded within well-designed learning environments, AI can support higher-order cognitive processes, including reflection, feedback uptake, and iterative knowledge construction (Mollick & Mollick, 2023). However, such benefits depend on students engaging critically with AI outputs, rather than treating them as authoritative or final (Perkins, 2023). Although the present study does not directly examine academic outcomes, prior research suggests that motivation-related processes, including procrastination, adjustment, and perceived employabilityare systematically linked to performance and well-being in higher education (Vlachopanou et al., 2025; Vlachopanou et al., 2026).

From a policy and institutional perspective, these findings further emphasise the importance of developing coordinated strategies for AI integration that are both discipline-sensitive and developmentally staged. Recent policy frameworks highlight the need to balance innovation with academic integrity, transparency, and ethical use (European Commission, 2026; EDUCAUSE, 2024; UNESCO, 2023; OECD, 2024). In this context, the present study supports a shift from viewing AI adoption primarily in terms of access or frequency toward understanding it as a matter of qualitative engagement, disciplinary alignment, and cognitive integration within evolving educational environments.

Without deliberate pedagogical design, generative AI risks not transforming learning, but stratifying it, amplifying the advantages of already AI-literate students while leaving others at the level of superficial engagement.

The study also offers methodological value. Much of the current literature relies on frequency counts, mean comparisons, or attitudinal scales. By contrast, Correspondence Analysis allowed us to visualise how tasks, platforms, confidence, usefulness, recency, and student characteristics formed broader behavioural configurations. This makes it possible to distinguish not only between more and less frequent users, but between qualitatively different ways of being an AI user in higher education. Such a configurational approach may be especially useful in a rapidly evolving domain where students combine tools and tasks in non-linear ways (Greenacre, 2017).

Several limitations should be acknowledged. First, the data are self-reported and therefore susceptible to recall bias and social desirability bias. Second, the sample was not balanced across gender and institutional sector, with women and private-institution students overrepresented, which may affect the generalisability of the configuration. Third, the study is cross-sectional and exploratory; the CA solution identifies association structures rather than causal mechanisms. Fourth, although the observed associations were statistically reliable, the effect size was modest, indicating that substantial within-

group variability remains. Finally, the instrument captured categories of use rather than direct measures of learning outcomes, academic performance, or ethical judgement, which constrains the conclusions that can be drawn about the consequences of specific AI use patterns.

Future research should build on these findings in at least three ways. Longitudinal studies could examine how profiles of use change as institutional guidance, platform affordances, and students' experience evolve. Mixed-methods designs could add explanatory depth by examining how students justify their use of AI within discipline-specific norms. Finally, outcome-focused studies are needed to test whether the patterns observed here translate into differences in academic performance, feedback uptake, writing quality, or self-regulated learning. A particularly important direction will be to determine whether targeted AI-literacy interventions reduce the gap between supportive and intensive users or whether they merely strengthen existing advantages.

Conclusion

This study profiled university students' academic AI use through Correspondence Analysis and demonstrated that use is patterned by discipline, confidence, perceived usefulness, recency, and platform choice. Two major profiles emerged: a technical–productive profile associated with Computer Science and business-related fields, and an academic-support profile associated with Humanities, Psychology, and Health-related disciplines. These findings indicate that AI use in higher education is not a single phenomenon but a differentiated set of practices shaped by both technological perceptions and disciplinary culture.

The study contributes to current debates on AI in higher education by moving beyond general claims of uptake and offering a relational map of how students actually use AI across disciplines. For institutions, the message is that policy, pedagogy, and student support should be discipline-sensitive, equity-oriented, and explicit about legitimate uses of AI in academic work. For researchers, the findings underscore the value of profiling approaches that can capture the heterogeneity of AI engagement in a rapidly evolving educational landscape. The critical challenge for higher education is therefore not whether students use AI, but how institutions shape the conditions under which such use becomes cognitively meaningful, ethically grounded, and educationally equitable.

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Clinical Trial Number

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Ethics approval

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Declarations

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Author Contribution

Laura Maska: Conceptualization, Project Administration, Writing – Review & Editing, Supervision. Maska led the conceptual development of the study and oversaw its academic and administrative coordination. Her expertise in “AI ethics and Higher Education” informed the study’s design and interpretive framework. She contributed to the critical revision and refinement of the manuscript.Dimitrios Kalamaras: Methodology, Formal Analysis, Data Curation, Writing – Original Draft (Methods & Results). Kalamaras designed and executed the statistical methodology, including data processing and correspondence analysis, drawing on his specialization in “Multivariate Data Analysis, Latent Variables, [and] Ordinal-Categorical data analysis.” He drafted the methodological and analytical sections of the manuscript.Patra Vlachopanou: Investigation, Literature Review, Writing – Original Draft (Introduction & Discussion). Vlachopanou conducted the literature review and contributed to the theoretical grounding of the study, informed by her research focus on “motivation, adjustment, learning, and problematic internet use.” She drafted substantial parts of the Introduction and Discussion.

Data Availability

The datasets generated and/or analysed during the current study are not publicly available because they form part of a broader research program that is still ongoing. Public release of the data at this stage would therefore be premature. The dataset will be made openly available in a public repository upon completion of the full research program. In the meantime, data are available from the corresponding author on reasonable request.

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Figures

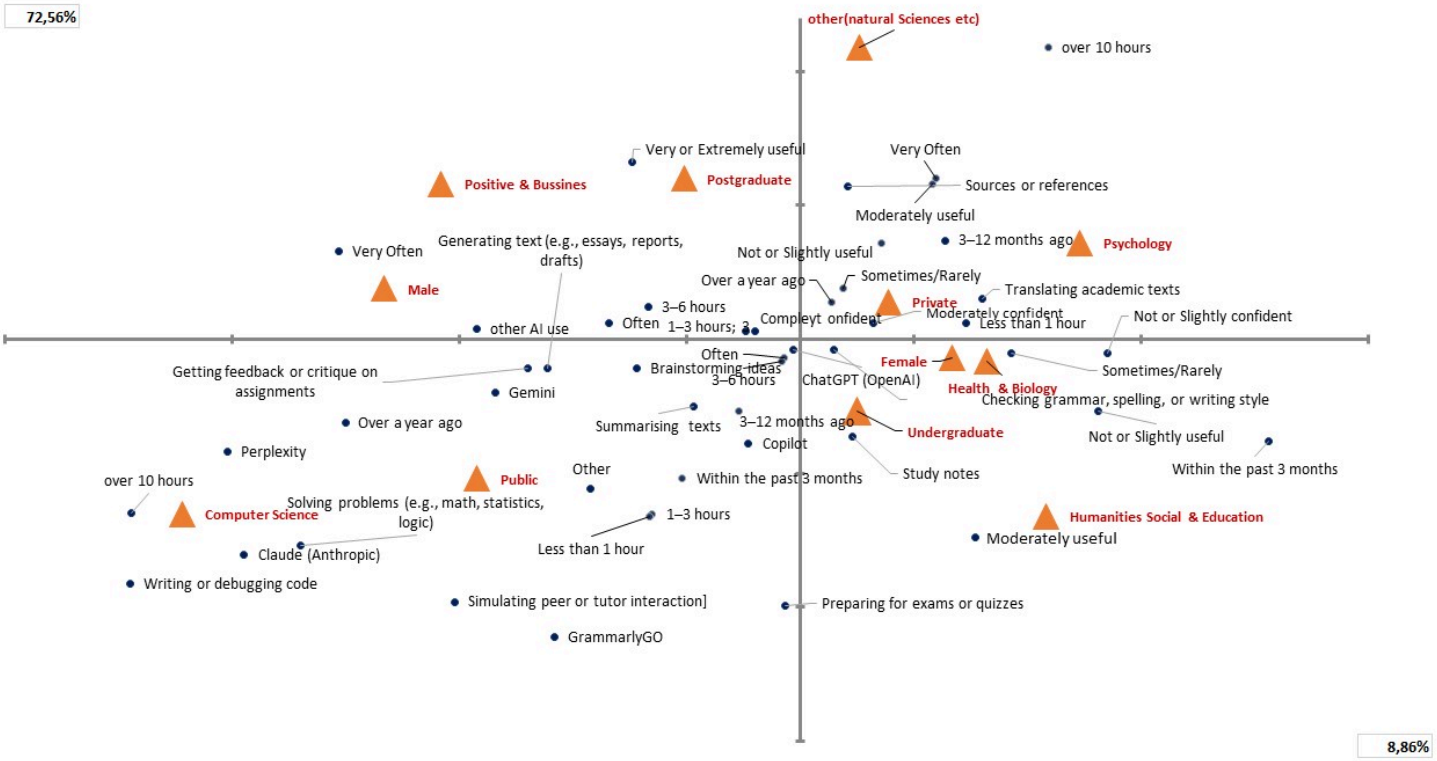


Figure 1

Two-Dimensional Correspondence Analysis Map of AI Usage Categories and Demographic/Academic Groups

Note. Blue circles represent AI-use Characteristics ; orange triangles represent demographic and academic categories. Dimension 1 (72.56% of inertia) differentiates intensive, high-confidence, technically oriented AI use from occasional, low-engagement, and supportive academic use. Dimension 2 (8.86%) reflects recency of use.