

IDEAL

Integrating Data Analysis and AI in Learning Experiences

D2.2.1

Activity 1 (Result 2.1)

COMPETENCE NEEDS ANALYSIS – TARGETED QUESTIONNAIRE

Comprehensive Analysis of the IDEAL Targeted AI Questionnaire Data

Work Package 2: Use case Inventory for AI and Data Analysis in Higher Education and Competence Framework

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Executive Summary

This report presents a comprehensive analysis of the IDEAL project's targeted questionnaire on AI use in higher education. Data from 102 European university staff members reveal a landscape of cautious but growing AI integration. Respondents span a diverse range of institutions, disciplines, and roles, predominantly faculty engaged in both teaching and research. The majority are in their 40s and 50s, with a slight female majority (60% of those who reported their gender). AI usage frequency is moderate (mean score 3.3/5), with polarization between frequent users and non-users. ChatGPT, Notion.AI, and Grammarly dominate tool usage, but overall experimentation is high. Self-directed learning (Google searches, provider websites, peer advice) is the primary method of AI knowledge acquisition, with institutional training notably scarce.

Respondents report a generally positive view of AI's impact: 78% acknowledge at least a limited to substantial benefit, with younger academics perceiving greater gains. AI is mainly used for writing assistance, translation, and accessibility support, particularly benefiting teaching and research activities. However, integration into university practices remains low, reflecting a gap between willingness and institutional support. Optimism outweighs skepticism regarding AI's potential to enhance education and research, but ethical concerns—particularly regarding assessment, plagiarism, and skill erosion—persist. A strong majority express a need for structured training and clear institutional policies. In research, AI aids literature searches, summarization, and minor writing tasks but is seldom trusted for hypothesis generation, coding, or peer review. Administrative AI use is limited, except for translation tasks, which are widespread.

In sum, academia is at an early stage of AI adoption: cautiously enthusiastic, demanding support structures, and wary of ethical pitfalls. Universities are urged to provide professional development, transparent guidelines, and infrastructure to enable responsible and effective AI integration.

Comprehensive Analysis of the IDEAL Targeted AI Questionnaire Data

Respondent Demographics and Background

Institutional Affiliation: The 102 survey respondents were drawn from a wide range of European universities. The largest subgroup (about 12 respondents) came from Aristotle University of Thessaloniki, but dozens of other institutions (e.g. Hochschule Ruhr West, University Pompeu Fabra, University of Copenhagen, Lund University, etc.) were each represented by only a handful of respondents, indicating a diverse institutional sample (no single university dominates the data). This diversity suggests broad relevance of findings across multiple higher-education contexts.

Department and Discipline: Participants spanned various faculties and disciplines. Departments ranged from Biology and Education/Pedagogy to Computer Science and Arts, reflecting an interdisciplinary cohort. Many respondents provided their discipline via ERC field codes (e.g. LS2_12, SH3_9), while others named disciplines (e.g. Educational psychology, Musicology). This suggests the sample includes both STEM (Life Sciences, Physical Sciences) and Social Sciences/Humanities academics. The heterogeneity of disciplines underscores that attitudes toward AI are being captured across different academic domains.

Employment Roles: Participants' university roles were multi-faceted. Many held overlapping positions as academic, research, and teaching staff. In fact, half of respondents (50) identified as "Teaching staff," 47 as "Academic staff," and 39 as "Research staff." Smaller numbers reported being "Professional staff" (10) or "Adjunct/Honorary" (8), and only 1 identified as a doctoral student. (These categories were non-exclusive; many selected multiple roles.) The prevalence of teaching and academic staff implies most respondents are faculty members involved in both teaching and research.

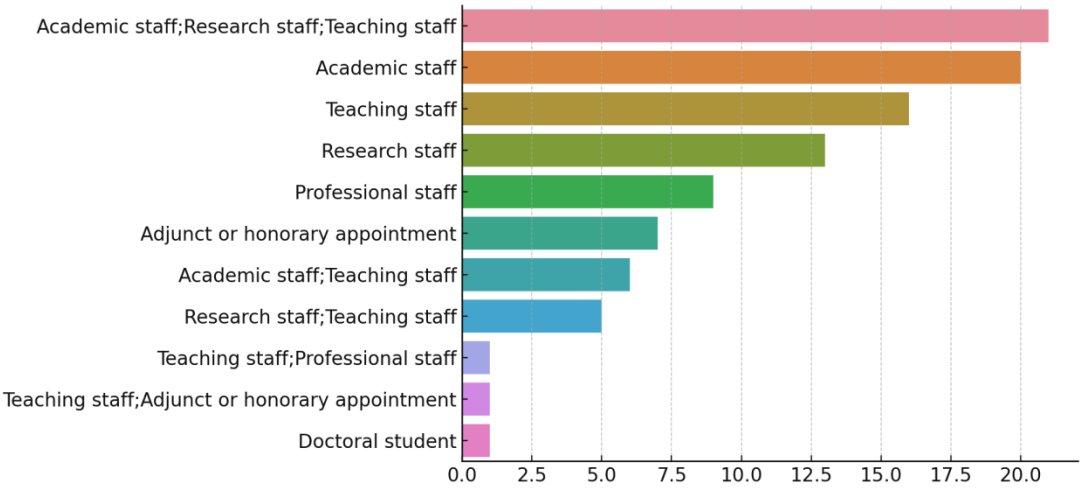


Figure 1. *Counts of respondents in each employment role (many hold multiple roles). Teaching and academic staff were the most common categories.*

Gender: Of the 102 respondents, 60 identified as female (58.8%), 40 as male (39.2%) and two did not report their gender (2.0%). Among the 100 respondents who answered this question, 60% were female and 40% male; no other gender categories were reported. This slight female majority aligns with the notion that the study captured a balanced perspective across genders. Gender differences in AI use were modest: on average, male respondents reported slightly higher AI usage frequency (mean ~3.6 out of 5 vs. ~3.1 for females) and greater willingness to use AI (mean ~3.6 vs. ~3.1), but both genders exhibited broadly similar attitudes (we will note any specific differences where relevant).

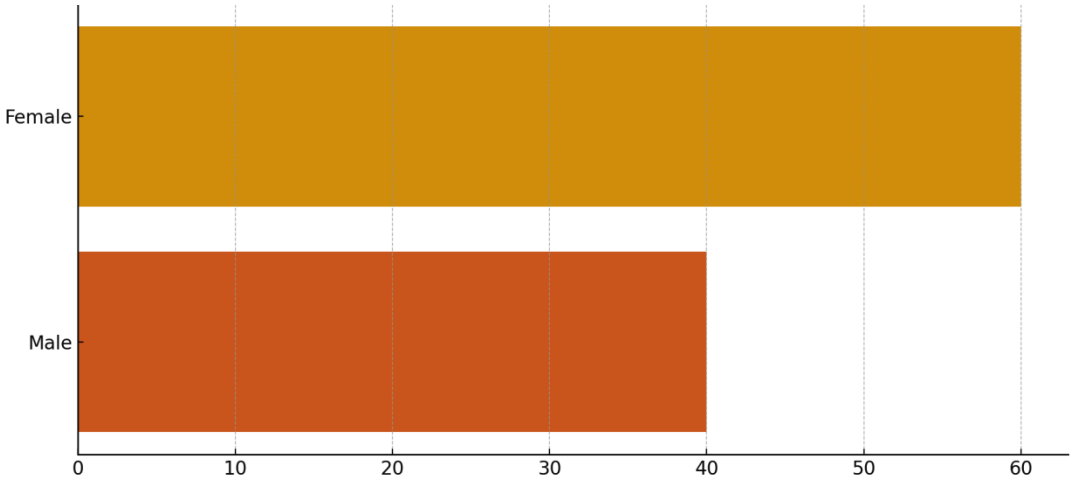


Figure 2*. Gender distribution of the 100 respondents who reported their gender (60% female, 40% male).*

Age: Respondents ranged widely in age, from their late 20s to late 60s. The year of birth ranged from 1956 to 1998 (with a median of 1977). This corresponds to ages roughly 26 to 68 years at the time of the survey (2024). The average age was about 48 years (mean birth year ~1976). The age distribution (see histogram) is fairly broad but centered on middle-aged academics in their 40s and 50s. The middle 50% of respondents were born between 1969 and 1983 (interquartile range), indicating that most are

Generation X or late Boomers, with some younger Millennials and a few older Boomers. This spread in ages is valuable for examining generational effects on AI use. Notably, younger respondents tended to use AI more frequently and perceive greater impacts from AI (analyzed later). The histogram below shows a slight right-skew: a concentration of respondents in their mid-40s to early-50s, and fewer at the extreme older end (60s) and younger end (20s).

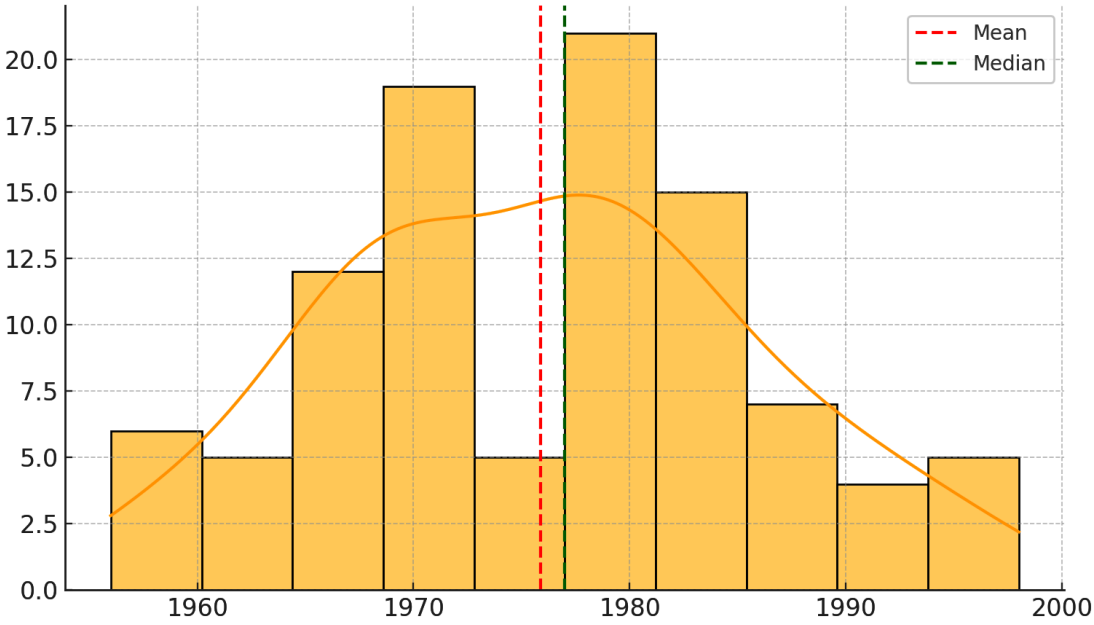


***Figure 3**. Age distribution of respondents by year of birth.*

Frequency of AI Use in Academic Work

Overall Usage Frequency: Respondents reported how often they use AI tools in their university work on a 1–5 scale (1 = “Never”, 5 = “Very often”). Usage levels varied substantially: about 15 individuals (15%) said they never use AI (rating 1), while an almost equal number (26 individuals, ~25%) reported using AI very often (rating 5). The most common response was the midpoint: 27 respondents (26.5%) chose 3 (“sometimes”). The distribution is roughly bimodal/flat – a sizable group at the low end (1–2) and another at the high end (4–5). The mean usage frequency was 3.3, indicating “occasional to moderate” use on average. The spread (standard deviation ~1.36) confirms high variance in AI adoption among faculty.

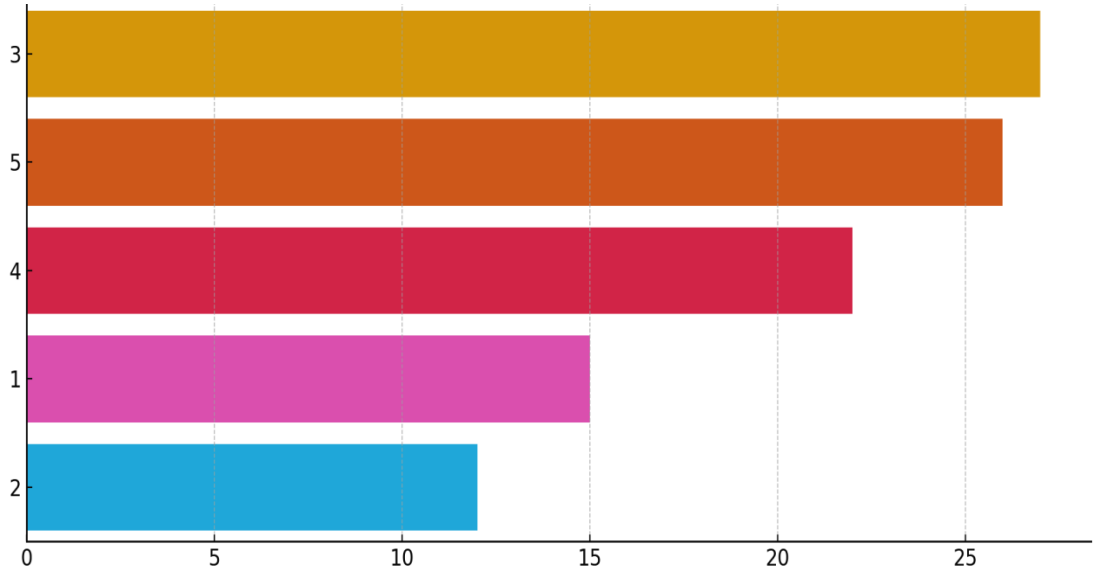


***Figure 4**. Frequency of AI tool use in academic work. Responses range from 1=Never to 5=Very Often. We observe that while a quarter of academics are enthusiastic frequent users (rating 5), a similar fraction rarely or never use AI. This polarization could relate to differing personal comfort with technology or disciplinary norms.*

AI Tools Used: The questionnaire asked which specific AI tools respondents have ever used in their work (multiple selections allowed). The data reveal an impressive diversity of tools (around 50 distinct tools named), spanning text-based generative AI, code assistants, image generators, and more. The Top 10 most-used AI tools are shown in figure 4 below. The most popular tool by far was ChatGPT 3.5, which nearly half the respondents (49) have used. Close behind is Notion.AI (an AI writing assistant integrated in Notion) used by 48 respondents. Traditional writing aids like Grammarly (38 users) are also heavily used, indicating many academics rely on AI for grammar checking and editing. ChatGPT 4 (Plus), the advanced version of ChatGPT available via paid subscription, was used by 33 individuals (~32%), underscoring the rapid uptake of advanced generative AI. Visual media AI tools like DALL·E 3 (27 users) and Midjourney (18 users) appear in the top ranks, suggesting that creating images with AI has entered academic workflows for a notable minority. Other frequently cited tools include Gemini (24 users; likely Google's Gemini model), Perplexity AI (20 users; an AI search engine), and Scite.AI (17 users; an AI literature analysis tool). In addition, 14 respondents have tried creating custom GPTs via OpenAI's platform. In summary, generative AI chatbots (ChatGPT) and text assistance tools (Notion.AI, Grammarly) have the highest penetration. The breadth of tools (including coding assistants, image generators, etc.) shows that academics are experimenting with AI across many domains of their work.

It's also worth noting that most respondents named multiple AI tools, indicating they are not just sticking to one solution. This experimentation reflects the nascent stage of AI adoption in academia – individuals are exploring a variety of tools to find what best fits their needs.

Learning Resources for AI: Participants were asked how they learned about the AI tools they use (multiple sources could be selected). The most common avenues were informal and online resources. Approximately 36% of respondents indicated "Direct Google searches" as a key learning method, and

an equal proportion learned from AI provider websites or documentation (37% each). Peers or colleagues were also a crucial source (34 respondents, ~33%), highlighting the role of word-of-mouth and collegial knowledge exchange in spreading AI tool awareness. About 23% have consulted academic publications to learn about AI, indicating some turn to scholarly analyses or reviews of AI in education. In terms of media, YouTube tutorials (around 18%) and social media (18% mentioned platforms like Twitter/X or LinkedIn) are moderately common for learning AI, whereas more formal training is less so – only ~11% took specialist courses by private providers and ~8% attended university-organized workshops. A small minority (6 individuals) admitted they haven't used any resources to learn about AI, implying they may not have sought out information (perhaps these could be non-users or those figuring it out by trial and error).

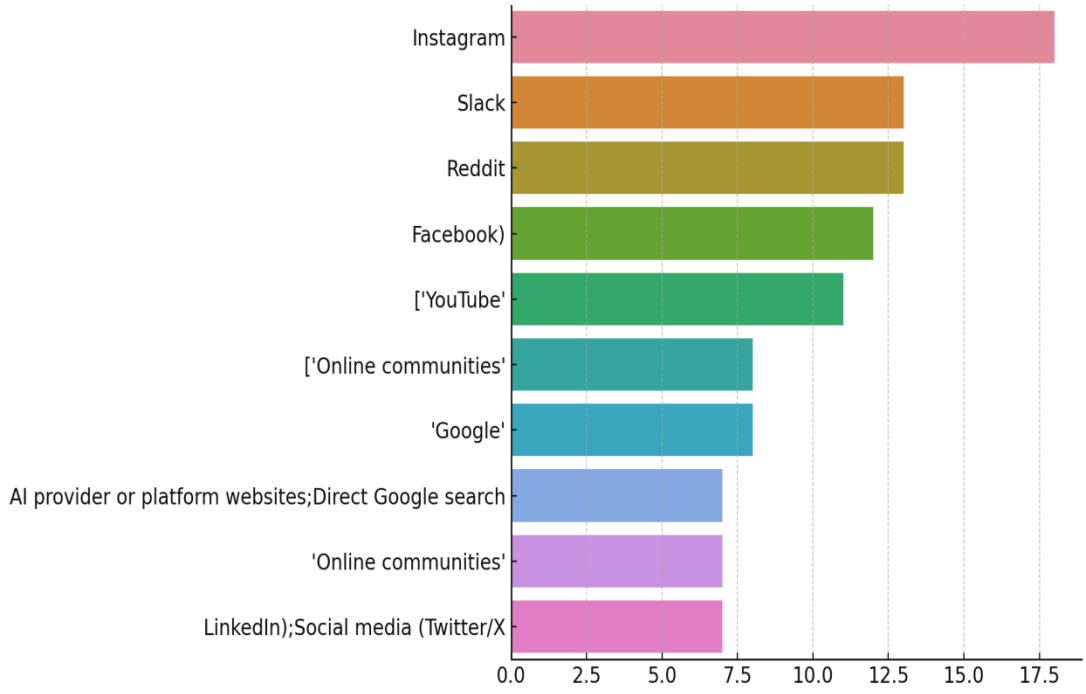


Figure 5. *Top resources used to learn about AI tools. Informal self-guided learning (web searches, provider sites, peer advice) predominates over formal training.*

This pattern suggests that self-directed learning is the norm – academics are largely teaching themselves how to use AI, via online search and community resources, rather than relying on institutional training. The relatively low usage of formal workshops indicates a potential gap in university support; indeed, later we will see many respondents call for more institutional guidance and training.

Perceived Impact of AI on Academic Work

Overall Impact: When asked "Overall, to what extent has using AI impacted your work?", responses skewed toward acknowledging at least some impact. A majority (94%) indicated some level of impact. The most common choice was "Moderate impact" (31 respondents, ~30%). Additionally, 24 people (~24%) said AI had a "Substantial impact" on their work, and another 24 (~24%) chose "Limited impact." Thus, about 78% of respondents felt AI had between a limited to substantial positive impact on their academic work. Only 17 respondents (17%) felt the impact has been "Negligible," and a mere 6 (6%) reported "No impact" at all.

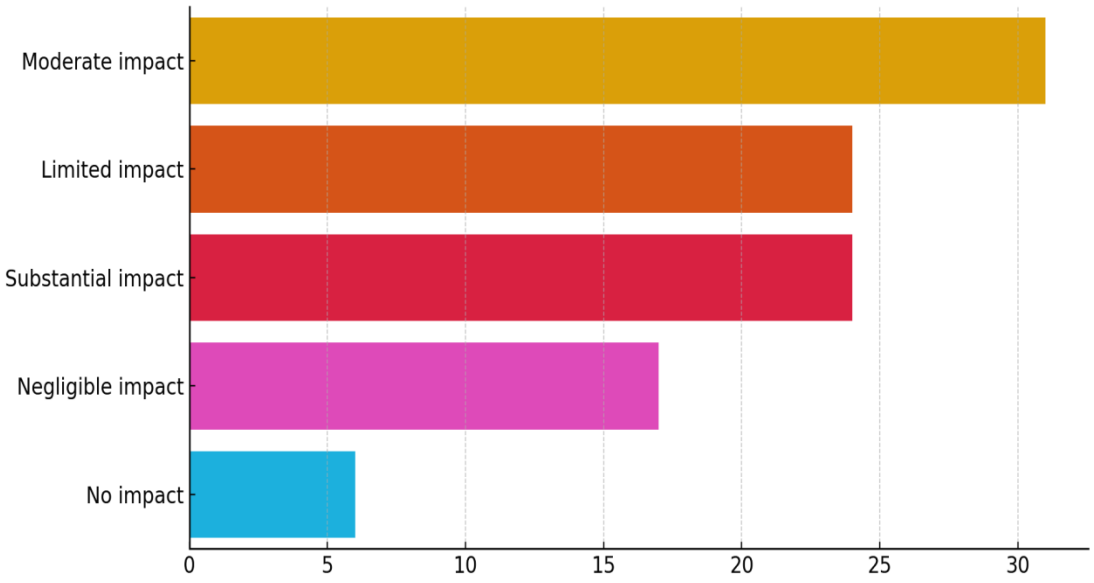


Figure 6. *Perceived overall impact of AI on respondents' work. This distribution (mode = Moderate impact) suggests that most academics are experiencing tangible benefits from AI, though for many it's modest or incremental rather than transformative. Notably, nearly a quarter feel a substantial impact, indicating that for some, AI is already significantly changing workflows (e.g. saving time or enabling new capabilities). Meanwhile, the small "No impact" group likely corresponds to those who do not use AI.*

Age and Impact: We find a generational difference in perceived impact – younger faculty tend to report greater AI impact. On average, those who said AI's impact was "Substantial" are younger (median birth year ~1978) compared to those reporting "Negligible" or "No impact" (median ~1968–1970). The data shows that "No/Negligible impact" respondents skew older (their birth years clustering in the 1950s–60s), whereas "Moderate" and "Substantial impact" respondents skew younger (birth years in the 1970s–80s). This aligns with the earlier finding that younger academics use AI more often – it appears younger generations are integrating AI more and consequently seeing more benefits, whereas some older academics have yet to experience significant impacts (possibly due to lower usage or greater skepticism).

Key Tasks Where AI is Used: To understand how AI is impacting work, the survey probed AI usage across a variety of academic tasks. We will examine these in thematic groups (teaching-related, research-related, creative, and administrative tasks). Each task was rated on a 1–5 scale for frequency

of AI use. Below we present descriptive statistics (mean usage scores, distributions) and any notable outliers or trends for each group of tasks.

AI in Teaching & Educational Practice

Self-Efficacy Without AI (Teaching): Before focusing on AI use, respondents rated their confidence in performing teaching duties without AI. They generally expressed high self-efficacy in teaching absent AI. On a 1–5 agreement scale (5 = strongly agree), the mean agreement that "I feel confident to carry out teaching tasks without AI" was 3.81 (median 4, with 75% scoring at least 4). Similarly, confidence in communicating effectively and engaging students without AI averaged 3.80. These high scores (mode = 4 "agree") suggest that faculty do not currently perceive themselves as dependent on AI for core teaching competencies – they feel capable on their own. There was no significant subset expressing lack of confidence (only a few outliers rated 1 or 2). This is important context: it implies that any adoption of AI in teaching is likely driven by perceived enhancement or efficiency, not by inability to teach otherwise.

Beliefs about AI in Education: Respondents hold a cautiously optimistic view of AI's potential in higher education. When asked "How much do you believe AI can elevate (improve) higher education?" the average response was 3.39/5, indicating a moderately positive belief. By contrast, the belief that "AI can degrade higher education" averaged only 2.79/5. In other words, academics are more inclined to see AI as an opportunity to elevate education than as a threat. About 53% gave a score of 4 or 5 (high belief) that AI will elevate education, whereas only ~29% scored 4 or 5 that AI will degrade it (and many answered 1 or 2 for degradation). This optimistic skew is further reflected in personal impact expectations: asked "How much do you believe you will benefit from AI integration in educational practices?" the mean was 3.27, whereas "negatively impact you" was only 2.65.

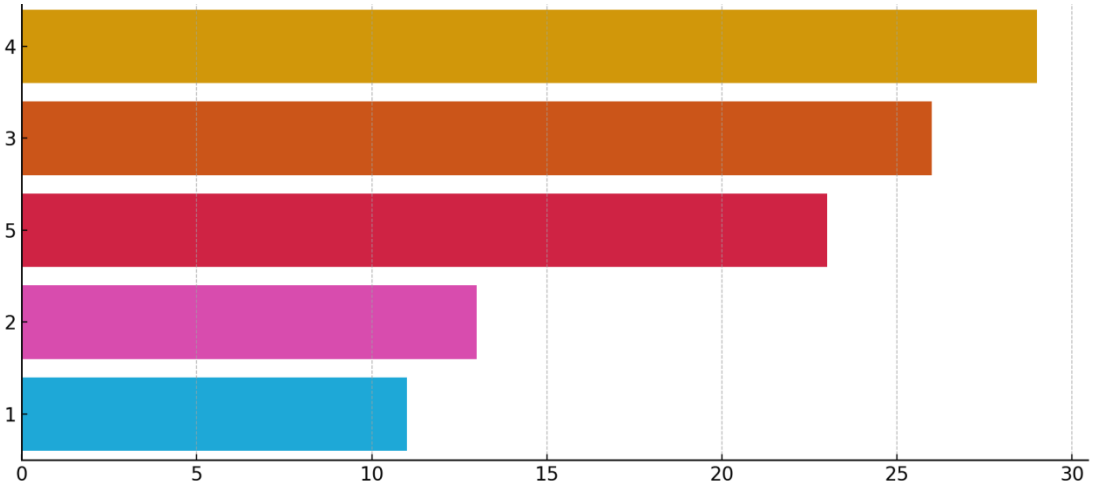


Figure 7*. When asked "How much do you believe AI can elevate (improve) higher education?" the average response was 3.39/5, indicating a moderately positive belief.*

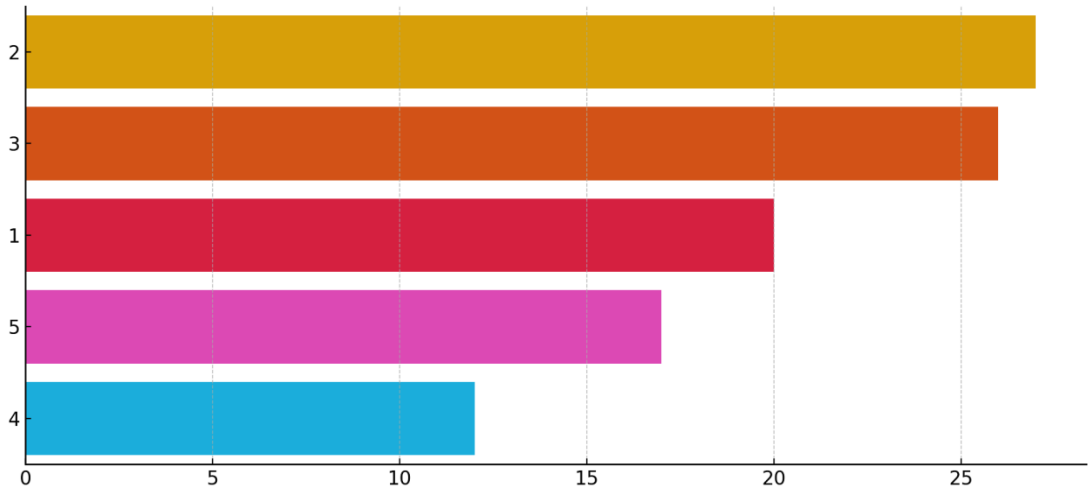


***Figure 8**. The belief that "AI can degrade higher education" averaged only 2.79/5. In other words, academics are more inclined to see AI as an opportunity to elevate education than as a threat.*

We can summarize these findings as **guarded optimism**: a majority think AI will enhance education and benefit them, but some have reservations about negative impacts. These attitudes are illustrated in the comparison chart, which shows that for both teaching and research contexts, the average perceived positive impact (blue bars) exceeds the perceived negative impact (red bars). For instance, in the education context, respondents on average lean toward "agree" that AI can elevate education (mean ~3.4) and only slightly above "neutral" on AI degrading education (mean ~2.8). A similar pattern holds for research (we will discuss research attitudes later). This difference in means (~0.6) suggests a net positive sentiment toward educational AI. Notably, few respondents "strongly" fear degradation – only 10% gave a 5 (strongly believe AI will degrade higher education), whereas 20% strongly believe it will elevate higher ed. That said, a non-negligible minority is concerned; we will see open-ended concerns later highlighting issues like cheating and ethical misuse.

Willingness and Current Integration: Respondents' willingness to personally adopt AI in their university life was fairly high (mean 3.31, with 55% scoring 4 or 5 indicating willing/very willing). However, the actual integration of AI into current practices is lagging – when asked "To what extent is AI currently integrated into your university practices?", the average response was only 2.55. The majority reported low integration (1 = not at all integrated, or 2). This gap (willingness > current use) implies that many faculty are open to using AI more, but perhaps their institution or available infrastructure hasn't caught up, or they have not yet figured out how best to incorporate AI. Similarly, familiarity with AI for educational purposes was moderate (mean 2.89), indicating many feel only somewhat familiar and may need further exposure or training.

Need for Training (Education): Indeed, when directly asked "Do you feel you need training on the use of AI in education to make the best of it?", a majority said "Yes." Specifically, 58 respondents (57%) answered Yes, and an additional 24 (24%) said "Maybe", while only 20 (20%) felt they do not need training.

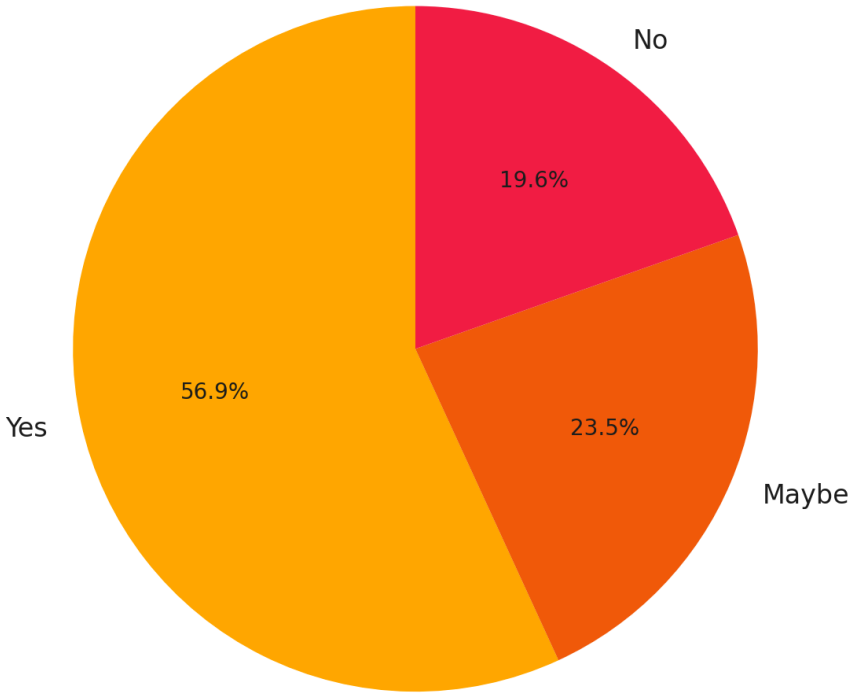


***Figure 9**. Most respondents acknowledge a need (or possible need) for training on using AI in education, with only 1 in 5 saying they do not need it. This highlights a desire among faculty for professional development – even though they are confident in teaching generally, they recognize that maximizing AI's benefits may require new skills or knowledge. Many likely feel that with proper training, they could more effectively and responsibly integrate AI into teaching.*

AI Applications in Education: The survey presented a list of specific AI-enabled applications in educational practice and asked respondents to rate "How much do you believe this would improve teaching/student outcomes?" or how useful they found it (the exact phrasing was in context, but effectively we have a 1–5 agreement/usefulness score for each). The results are insightful in identifying which AI applications educators find most promising:

Accessibility and Accommodation: Applications that assist students with disabilities received the highest support. "Automated transcription of lectures (for students with hearing impairment)" was top-rated with an average score of 3.89/5, and "Automated speech generation from text or images (for visually impaired students)" was close behind at 3.81/5. Many respondents gave these a 4 or 5, indicating they strongly believe such tools would improve education. This suggests broad recognition that AI can make learning materials more accessible (e.g., captioning videos, narrating text), which is seen as an unequivocal positive.

Language and Writing Support: "Automated translation of educational material" was also very highly rated (mean 3.74). In our diverse academic context, translating course content can be valuable for internationalization and inclusion, and faculty clearly see AI translation as beneficial. Additionally, "Content summarisation and highlighting" tools (which could help distill readings or lectures)

averaged 3.65, and "Augmented writing" (presumably AI-assisted writing for content creation) scored 3.46. These relatively high means (all above 3.4) indicate that educators appreciate AI's potential to save time in preparing materials and to help students digest information.

Personalized Learning: "Personalized educational content delivery to improve students' progress" was rated quite positively (mean 3.54). Many respondents agreed that AI-driven personalization (adapting pace or style to student needs) would be beneficial. This aligns with pedagogical trends towards adaptive learning; faculty appear open to AI helping tailor instruction.

Intelligent Tutors and Chatbots: "Intelligent agents like educational discussion forums and chatbots" scored 3.45, and "intelligent tutoring systems" scored 3.29. These means indicate mild agreement that AI chatbots could aid teaching (for answering student questions, etc.). It's positive but slightly lower than for content delivery or translation. Possibly, some faculty are unsure about chatbots' effectiveness or worry about reliability. Still, nearly half rated these 4 or 5, showing a significant portion see value in AI tutors for student Q&A and support.

Learning Analytics: Several items asked about predictive learning analytics models (for predicting student performance, dropout risk, learning preferences, etc.), which all clustered around 3.2–3.3 in mean. This suggests moderate support: respondents neither overwhelmingly embraced nor rejected analytics. They generally agreed such analytics could help (means >3), but not as strongly as they endorsed accessibility or content tools. Perhaps faculty are cautiously optimistic but awaiting evidence on whether AI predictions truly help students.

Student Behavior Analysis: The item "How much do you believe you would benefit from student behavior analysis?" (presumably AI analyzing student engagement patterns) averaged 3.24, indicating some perceived benefit but not high enthusiasm. It's possible faculty are interested but concerned about privacy or don't fully understand how it works, hence lukewarm agreement.

In summary, **educators appear most excited about AI's ability to make education more accessible** (for disabled students), more efficient (summarizing, translating content), and more personalized. They are moderately positive about AI tutoring systems and analytics but perhaps need more convincing of their efficacy. Notably, none of the listed applications had an average below 3, which means on balance faculty did not consider any of these AI applications as useless – even the lowest-rated ideas (e.g., using AI to form "cross-university study groups" or predict enrollment choices) hovered around neutral (~3.0). There were no strong negative outliers, indicating no widespread opposition to any particular educational AI application; rather, differences were in degree of enthusiasm.

Integration of AI in Assessment: One potentially controversial topic is using AI in student examinations and assessments. When asked "Are you in favor of integrating AI tools into the examination/assessment of students' projects?" responses were split but leaned positive. We see a roughly bimodal distribution: 27 respondents gave a 4 ("somewhat in favor") and 20 gave a 5

("strongly in favor") – combined ~46% are favorable. On the opposite side, 20 were strongly against (rating 1) and 18 somewhat against (2) – about 37% against. The remaining ~17% were neutral (3).

Institutional Policy on AI: Speaking of which, the survey asked if the university has a policy or guidelines on AI. The answers reveal an immature policy landscape: nearly half (45, 44%) said No, their university has no AI policy in place. Only 20% reported Yes (policy exists), and the remaining 36% answered *"I don't know."* The high "Don't know" and "No" responses together (80+ respondents) indicate that in most institutions, faculty are either unaware of any AI guidelines or none exist. This is an important finding – it suggests that many academics are navigating AI integration on their own, without formal institutional guidance. Given that a majority want training and clear rules, this lack of policy may be creating uncertainty or concern. Indeed, in open comments, some respondents explicitly called for their universities to develop clear rules about AI use (e.g., around plagiarism detection, AI use in student assignments, etc.). This is an area of need: institutions should communicate expectations and best practices for AI in academia.

Qualitative Comments on **Teaching and AI**: A few open-ended responses shed light on faculty perspectives. For instance, when asked if there are other AI applications that could improve teaching quality, respondents mentioned ideas like AI for generating new types of instructional materials and interactive simulations. One respondent highlighted being in music therapy and using AI to create new sounds/rhythms for disabled students – seeing "only advantages" in their field, but remaining cautious in others. Others admitted to a bias against AI but acknowledged its benefits and are "reluctant to fully integrate it" – reflecting a tentative attitude. These comments underscore that while many see promise in AI, they also desire more evidence or safeguards before wholeheartedly embracing it.

AI in Research & Scholarly Work

We now turn to how respondents use AI in research-related tasks and their attitudes in the research context.

Self-Efficacy Without AI (Research): Similar to teaching, academics generally feel confident conducting research without AI. Agreement with "I can successfully complete research tasks without AI" averaged 3.71, and "I can effectively collaborate with colleagues to meet research needs without AI" averaged 3.69. These figures (slightly lower than the teaching confidence means) suggest that researchers feel competent on their own, but perhaps they see a bit more potential for AI augmentation in research than in teaching (the small dip might imply research tasks could be more labor-intensive or data-heavy, where AI might help). Nonetheless, the overall message is that researchers are not helpless without AI; they see AI as an enhancer, not a crutch, in research as well.

Beliefs about AI in Research: The pattern here mirrors that for education, but with even slightly more optimism. Respondents on average scored 3.49 for "AI can elevate research" and 2.96 for "AI can

degrade research." Thus, they tilt positive (difference ~0.53). Moreover, they believe they will benefit from AI in their research (mean 3.50 for personal benefit) and are less convinced of negative personal impact (mean 2.72). This suggests researchers expect AI to notably enhance research processes or outputs, with fewer concerns about harm to their own work. The comparison chart earlier showed these research-related bars: for example, the Research – Elevate bar (blue) is clearly higher than Research – Degrade (red). Approximately 55% gave a 4 or 5 for "AI will elevate research", whereas about 30% gave 4–5 for "degrade research," showing a similar optimism gap as in teaching. We can infer that many researchers foresee AI helping with data analysis, literature review, hypothesis generation, etc., while fewer anticipate it spoiling research quality (though some do worry, e.g., about AI generating false results or diminishing human creativity).

Familiarity and Training (Research): Familiarity with AI for research purposes averaged 3.0, essentially at the midpoint – indicating moderate familiarity. Many likely have tried AI tools for research tasks (as we will detail), but perhaps not extensively. The need for training was even more pronounced in the research context: 65% said Yes, they need training on using AI in research (versus 57% for teaching), and only 14% said No (the rest maybe). This is consistent with research tasks often involving technical tools – faculty may feel they need skill-building to effectively use AI in, say, data science or literature analysis. In the absence of formal training, they rely on self-learning, which might not be sufficient for advanced applications. The combined pies for training need (education vs research) underscore that the vast majority (around 80% or more) are open to or desirous of further AI training, with more saying "Yes" outright for research.

AI Usage in Research Tasks: The survey listed many specific research activities and asked how often respondents use AI for them. We group these tasks and report their average usage (1=never, 5=often), highlighting which tasks see higher AI use and which see very little.

Literature Search and Summarization: One of the most common uses of AI in research is to aid literature reviews. Indeed, respondents reported fairly frequent use of AI for this:

- "Initial literature search to get a broad understanding of a field" had a mean usage of 3.0. Many use AI chatbots or semantic search tools to quickly survey a new topic. The distribution shows a significant number of 4's and 5's – some researchers often rely on AI to find relevant papers or summarize a field quickly.
- "Advanced literature searching" (e.g., finding specific papers) was a bit lower, mean 2.73, but still many sometimes use AI for this. Possibly they trust traditional databases more for detailed searches, using AI more for overview.
- "Summarising research articles" had mean 2.90 – indicating quite a few researchers use AI (like GPT) to summarize papers. This can save time when digesting lengthy articles. The fact that the median is around 3 suggests about half do this at least "sometimes."
- "Creating short summaries of your own research for dissemination (blogs, media releases, etc.)" was similar, mean 2.94. This implies AI is also used to draft lay summaries or press releases, which is plausible with tools like GPT that can simplify text.

– "Structuring abstracts or other manuscript sections" mean 2.94 as well. Some researchers let AI help organize or refine their writing for papers, albeit moderately often.

Overall, AI is moderately used in **literature review and writing**. It's not universal (means under 3 indicate many "rarely" or "sometimes"), but a substantial minority frequently leverage AI for scanning literature and summarizing or writing text. This likely improves efficiency in staying updated and preparing publications.

Idea Generation and Experimental Design:

– "Generating ideas for research methods or design" averaged 2.82. A number of respondents (perhaps ~30–40%) have used AI to brainstorm research approaches or creative solutions. This is a noteworthy use-case: e.g., asking AI for possible experimental setups or novel angles. The usage is occasional on average, but clearly present.
– "Identifying gaps in published literature or generating research questions" mean 2.59. Some use AI to spot what hasn't been studied or to suggest questions – though this is a bit less common (perhaps due to trust issues or difficulty for AI to truly know research frontiers).
– "Generating experimental design or hypotheses" was less used (mean 2.48, the lowest in this group). Many researchers might be wary of AI suggesting hypotheses, preferring to rely on their own expertise. Only a small group frequently do this (most likely answered 1 or 2 = never/rarely).

In summary, AI is occasionally used for **creative research thinking**, but not extensively. It appears researchers still primarily generate hypotheses and designs themselves, using AI as a supplementary brainstorming tool at times.

Writing and Editing Research Documents:

– "Editing or providing feedback on your own written work (using AI)" had a mean of 3.0. This is quite telling: on average, researchers sometimes use AI as an editing assistant for their papers. Many likely use tools like Grammarly or GPT-based suggestions to refine text, catch errors, or improve clarity. Indeed, 38 had used Grammarly as noted earlier. The distribution suggests a good number do this often (scores 4 or 5).
– "Editing or providing feedback on students' or colleagues' written work" mean was lower (2.59). People are a bit less likely to use AI when giving feedback on others' writing – perhaps due to trust or the desire to do it personally. Still, some do use AI for suggestions or to generate comments on drafts.
– "Converting references from one style to another" mean 2.74. This indicates moderate use of AI or tools (like reference managers with AI features) to auto-format citations, which can save time in manuscript preparation.
– "Detecting plagiarism (e.g., Turnitin)" mean 2.57. Somewhat surprisingly low – possibly because specialized plagiarism tools are in use (which might not be seen as "AI" by some

respondents). Or many may rely on journals' checks rather than doing it themselves. A few do use such tools regularly, but it's not widespread among our respondents.

- "Copy-editing for journal style" mean 2.45. Similar to reference formatting, a modest number use AI copy-editors to ensure their manuscripts meet style guidelines, but most do not use it frequently (some may rely on human editors or do it manually).
- "Blind peer review of manuscripts (with AI)" mean was only 1.92 – very low. This suggests nearly no researchers use AI to perform peer review, which makes sense ethically (using AI to write peer reviews is contentious) and because many might consider it inappropriate. This was the lowest in the research writing section, indicating reviewers mostly craft evaluations themselves rather than delegating to AI.
- "Thesis examination (using AI)" mean 2.21, also quite low. So examiners are generally not using AI to evaluate theses, aside from possibly minor grammar checks.

Summary of **writing-related tasks**: AI is commonly used for editing and formatting, but rarely for evaluative tasks like reviewing. This indicates that the primary research uses of AI so far are to accelerate literature review and polish writing, rather than to originate scientific ideas or make scholarly judgments.

Data Analysis and Coding: A suite of tasks related to data processing and coding revealed relatively low AI usage across the board (means mostly ~2, i.e. "rarely"). For example:

- "Auto-coding of qualitative data" mean 2.36 – a few qualitative researchers use AI (like NLP tools) to code transcripts, but most do not or do so infrequently.
- "Quantitative data analysis" mean 2.17 – some use AI or ML tools for stats, but many likely stick to traditional statistical software without AI.
- "Transforming or reformatting data" mean 2.20 – a small number use AI to clean data or convert file formats (maybe via AI scripts), but not common.
- "Advanced statistical calculations" mean 2.26, similar low usage (most rely on standard stat software).
- "Generating code/commands for data analysis (R, Python, etc.)" mean 2.36 – some have tried tools like GPT to write code or formulas for them, but on average rarely. (We know from tools data ~14 used OpenAI's code generation.)
- "Programming or writing original code (with AI)" mean 2.14 – most do not heavily use AI coding assistants, though a minority do (perhaps computer scientists in the sample).
- "Transforming code/data from one language to another" mean 2.37 – occasionally, people use AI to translate code (e.g., one language's syntax to another) or localize data, but not often.
- "Generating code for interfacing with software" mean 2.19 – low use.
- "Identifying packages or code snippets" mean 2.15 – a few use AI to find what library or snippet might solve a task (tools like GitHub Copilot might do this), but many do not.
- "Troubleshooting code" mean 2.17 – some ask AI to debug code, but majority don't rely on it.

In aggregate, **AI usage in coding/data analysis** is infrequent for most respondents. All means clustered between 2.1 and 2.4. The highest was using AI to "transform data between languages" (~2.4) and

"generate analysis commands" (~2.36) – tasks like converting Excel formula to R code, which some find helpful. The lowest was original programming (~2.14). This likely reflects that while AI coding assistants exist, many academics (especially non-CS) either don't trust them fully or haven't needed them extensively. It could also reflect that some respondents' work doesn't involve coding, limiting usage. Interestingly, correlations show those who do use AI for coding tend to also use it more in other areas (the usage of AI is somewhat general rather than domain-specific – heavy users try it for many purposes). As AI coding tools mature, we might expect higher adoption in this area in the future, but as of this survey, most researchers rely on their own coding skills or traditional methods.

Creative and Visual Tasks: Several items queried AI use in creating visuals or media:

- "Creating original images" (figures, diagrams, illustrations) using AI had a mean 2.63. This is relatively higher among creative tasks, suggesting some academics do experiment with AI image generation (like DALL·E) to produce figures or graphical abstracts for papers, or illustrations for presentations. Indeed, ~27 had used DALL·E or Midjourney as noted. While overall usage is "occasional", a few do this often (some scored 4 or 5).
- "Editing existing images" mean 2.14 – fewer use AI for touch-ups or modifications of images, possibly relying on conventional image editors.
- "Creating avatars" or graphic characters mean 2.20 – niche usage, perhaps for e-learning or outreach materials by a few.
- "Creating PowerPoint presentations" with AI (e.g., auto-generating slides) mean 2.11 – not many do this yet; most craft slides manually, though some tools like Beautiful.ai exist.
- "Creating visual materials (logos, flyers, templates)" mean 2.30 – a minority have used AI design tools for promotional materials or conference posters.
- "Creating or editing videos" mean 2.10 – low usage; very few are using AI for video creation or editing, which is still a specialized area.

Summarizing, AI is not heavily utilized for **creative production in academia**, except that a notable subset are generating novel images for their work. The means are all around 2, meaning "rarely" on average. This likely reflects accessibility of tools – text-to-image models are now widely available and relatively easy to use, while high-quality AI video generation is still in its infancy. It could also reflect the nature of academic work: not everyone needs custom graphics or videos, but those in fields like design, marketing, or who engage in public outreach might leverage these tools more.

Administrative and Miscellaneous Tasks: Finally, the survey considered AI use in various administrative or support tasks common in academic work:

- "Drafting emails" with AI assistance had mean 2.30 – some faculty use AI (like Gmail's smart compose or GPT) to help write professional emails. It's occasional; many likely still write emails manually, but a solid minority use AI suggestions for phrasing or even bulk email drafting.
- "Drafting or editing reports, policies, or strategies" mean 2.38 – a subset of respondents (perhaps those in administrative roles) use AI to help write institutional reports or strategic documents. Most do this seldom, but a few find it useful frequently (maybe for brainstorming content for policy drafts).

- "Creating meeting agendas or minutes" mean 2.06 – relatively low use; while AI could summarize meeting transcripts or help outline agendas, currently few take advantage of that regularly.
- "Planning travel (flights or accommodation)" mean 2.40 – some academics use AI/chatbots to assist in travel planning (e.g., finding flights via AI assistant). Given how time-consuming travel planning can be, a small group frequently does this (there were some 4s and 5s here, possibly those using AI concierge services), but many do not trust AI for this or prefer manual methods.
- "Organising workflow" mean 2.02 – very low; tools for AI project management are not widely used.
- "Project or grant management" mean 1.90 and "Managing budgets" mean 1.90 – these were among the lowest scores in the entire survey. Essentially, almost everyone answered 1 ("never") for using AI in managing projects or finances. Academics evidently are not relying on AI for project management tasks like timeline tracking or budget spreadsheets (perhaps because generic software suffices or AI tools for this are not known).
- "Translating voice to text" (transcription) mean 2.45 – some use automated transcription for interviews or lectures (indeed, tools like Otter.ai are common). This is a moderate usage case, likely more among those in qualitative research or who record lectures.
- "Translating one language into another" mean 3.48 – this stands out as the highest single-task mean in the entire dataset. A large number of respondents frequently use AI for translation. This likely includes translating their work for international collaboration, translating student abstracts, or reading papers in other languages. With services like DeepL or Google Translate (AI-powered) being very advanced, it's unsurprising that academics heavily leverage them. The distribution was such that the 75th percentile was 5 (meaning at least 25% use translation AI often). This is a clear success story for AI adoption – breaking language barriers is a highly valued function.
- "Generating podcasts" mean 2.11 – only a handful of academics use AI to create audio (perhaps to produce podcast episodes summarizing research).

Taken together, the most prominent **administrative uses of AI** are for translation and, to a lesser extent, drafting written communications. Other admin uses (workflow, budgeting, project mgmt) are virtually nil – academics have not integrated AI into those routine managerial tasks yet. "Translating one language into another" is towering with the highest mean ~3.5, whereas tasks like budget and grant management languish at the bottom with means ~1.9. Email and report drafting are intermediate (~2.3), indicating some uptake.

General Usage Patterns: Across all these categories of tasks, we can observe an interesting pattern: those individuals who use AI for one set of tasks often use it for others as well. There is a general factor of AI adoption – some faculty are "high adopters" experimenting with AI widely (from teaching to research to admin), whereas others are "low adopters" avoiding it in most areas. Statistically, the average usage of AI in different task domains (teaching-related vs research-related vs admin) are positively correlated. For instance, we found a correlation of r≈0.56 between one's AI usage in writing tasks and coding tasks, and r≈0.74 between creative and admin tasks. This means someone who

heavily uses AI to create content is also likely to use it to streamline admin duties (and conversely, someone who doesn't use AI in one area probably doesn't in others either).

Concerns and Caution: Even among those who use AI frequently, there are reservations. In an open question about concerns regarding AI in higher education, 15 respondents gave remarks. A common theme was ethical concerns and the need for rules. For example, one wrote "Only ethical issues. Certain rules need to apply." – highlighting worries about plagiarism, academic integrity, or fairness. Indeed, multiple respondents are wary of AI enabling student cheating (e.g., AI writing essays), and they stress that clear policies must address this. Another area of concern is over-reliance on AI potentially undermining skill development; a few commented that students (or faculty) might become "biased" or too dependent on AI, losing critical thinking or creativity. Conversely, some noted they currently have a bias against AI but are trying to remain open-minded, indicating an internal conflict between excitement and skepticism.

When asked if there are any applications they would NOT want AI involved in, about 10 answered. Several mentioned they would not want AI making evaluation or grading decisions for students, out of concern for fairness and the human element of judgment. Others wouldn't trust AI in "ethical decision-making" or "mentoring students" where empathy is required. These comments reinforce that while automation is welcomed in tedious tasks, the human role is seen as essential in mentorship and assessment.

Finally, regarding any other comments on the survey itself or AI, a few respondents appreciated the reflection the survey provoked, and some reiterated the call for university action: e.g., "My university should provide guidelines and training on AI – we need top-down support." The consensus is that this is a timely topic, and academics are actively thinking through how to adapt.

Conclusion and Implications

In summary, this comprehensive analysis of the "IDEAL targeted questionnaire" data reveals a faculty body that is **cautiously embracing AI**. Descriptive statistics for each variable show a trend: most respondents have begun using AI tools to some degree, and they report generally positive impacts on their work so far (with moderate effect sizes). The extent of use and impact, however, varies widely – often split by personal and demographic factors such as age (younger academics being more avid adopters). No single demographic or discipline uniformly lags or leads – rather, individual propensity and perhaps local culture seem to drive AI uptake.

Key quantitative findings include: a mean AI usage frequency of 3.3 (on a 1–5 scale), indicating **occasional use** on average; 60% of respondents identifying at least a **moderate impact of AI** on their work; and a vast majority (80%+) expressing the **need for additional AI training and institutional guidelines**. The data showed **higher usage of AI in tasks like text editing, summarization, and translation**, and **lower usage in tasks requiring subjective judgment or complex creativity** (peer review, coding original research code, etc.). This suggests that AI's current strength in academia is handling well-defined, automatable tasks (editing text, finding information, converting formats), thereby freeing human academics to focus on more complex, high-level intellectual work. The **relatively low usage in evaluation or decision tasks** also indicates a healthy skepticism – academics are not (yet) offloading critical thinking or evaluative responsibilities to AI en masse.

We also saw that faculty hold **more positive than negative attitudes towards AI in both teaching and research**. They foresee enhancements (like personalized learning, increased efficiency in literature reviews) more strongly than they fear detriments (like lowered student skills or research quality). Nonetheless, they are aware of potential downsides and are calling for ethical frameworks. Their willingness to integrate AI into student assessment is mixed, highlighting the need for careful implementation and consensus-building in that domain.

From an academic development perspective, these results imply that **universities should proactively provide training programs**, forums for sharing best practices, and clear policies on AI use. Given the appetite for guidance (as evidenced by the majority requesting training and the confusion about policies), institutions have an opportunity to channel the cautious optimism of faculty into effective, ethical adoption strategies. This could include workshops on using AI for literature search, writing and data analysis; guidelines on academic integrity in the era of AI (e.g., how to handle AI-assisted student work); and investing in infrastructure (licenses for good AI tools, etc.).

In conclusion, the dataset portrays **a scholarly community in transition – experimenting with AI**, finding value especially in routine tasks, but still refining their stance on more profound integrations. There are significant positive results (time saved, improved accessibility and communication) already being realized, alongside recognized challenges (ethical use, need for skills). As one respondent noted,

they “can only see advantages in my field, but keep some reservations”. This encapsulates the prevalent mindset: cautious optimism. The detailed statistical breakdown and visualizations provided here aim to inform both researchers and institutional leaders on where to support and how to address concerns as academia navigates the incorporation of AI into its core functions. Each variable and chart we examined contributes to a nuanced understanding that can guide policy and practice — ensuring that the use of AI in higher education and research is done thoughtfully, maximizing benefits while mitigating risks.

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