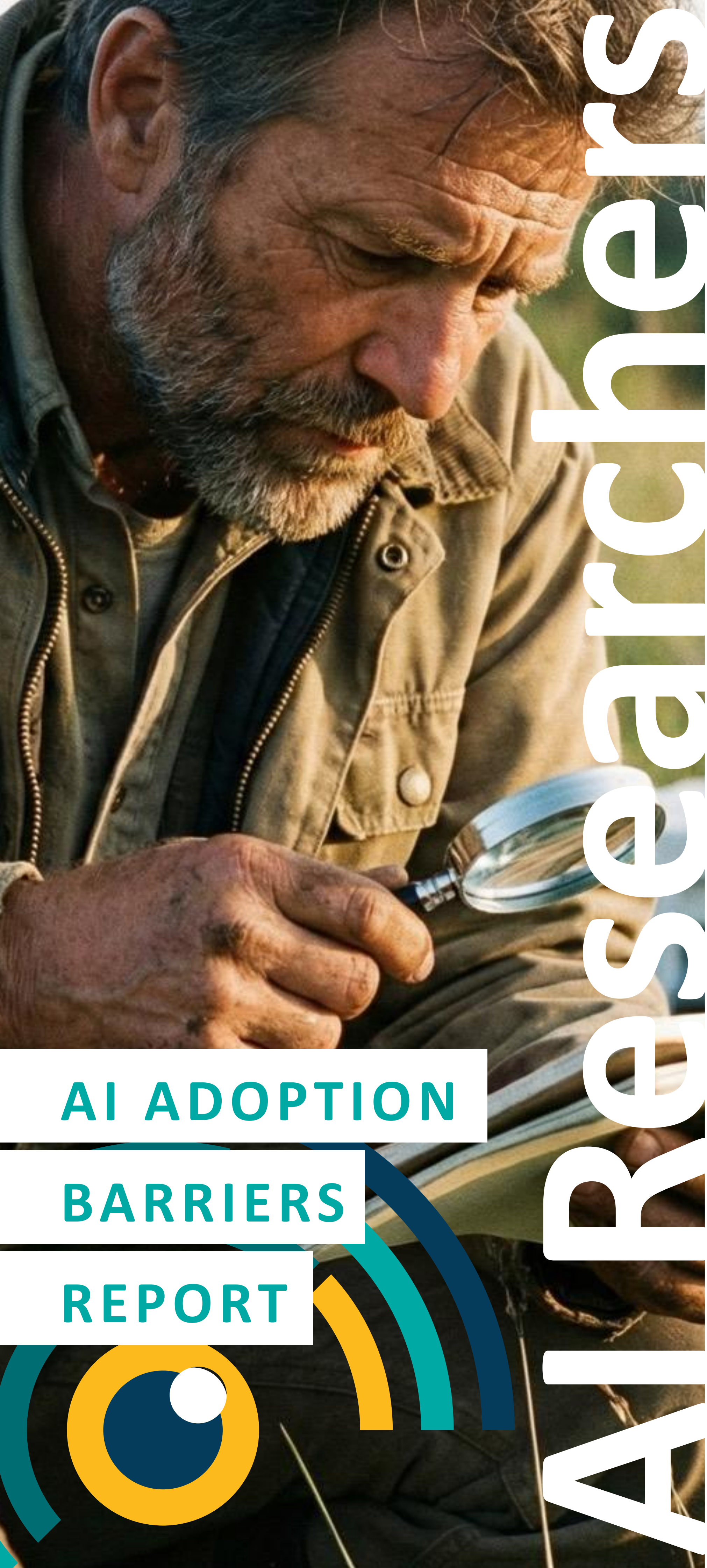

AI ADOPTION BARRIERS REPORT

AI Researchers
Embedding Responsible AI in Research

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01

INTRODUCTION

GENERATIVE AI IN AN ACADEMIC WORLD – CONTEXT OF THE STUDY

Generative Artificial Intelligence (GenAI) has quickly gone from being a niche technology to a tool that millions of people use every day. Systems like large language models (LLMs) and AI-powered assistants for writing, coding, and data analysis are now a regular part of how many people work - and their growing presence is sparking real debate. What does it mean to produce knowledge when an AI can help generate text, summarise literature, or write code in seconds? These are not abstract questions. They have practical consequences for how we think about expertise, authorship, and intellectual effort.

In academic settings, these questions carry even more weight. Universities and research institutions are built on the idea that the knowledge they produce is reliable, original, and earned through careful, honest work. That reputation is central to everything they do - from educating students to informing policy and advancing science. When a technology like GenAI enters this environment, it does not just offer new tools. It also challenges some of the assumptions that academic work has long been built on. The full implications of this shift are still being worked out, and researchers themselves are only beginning to understand what it means for their day-to-day practice.

This study was designed to explore exactly that - how researchers working in academia today actually relate to GenAI tools. Rather than focusing on what these tools can do in theory, we wanted to understand what is happening in practice: Are researchers using GenAI? If so, how and for what? If not, why not? What concerns or reservations do they have, and where do those concerns come from? To answer these questions, we combined Focus Group Interviews with a survey, using both qualitative and quantitative methods to get as complete a picture as possible of researchers' real experiences and attitudes. The aim was to build an honest, evidence-based account of the barriers and opportunities that currently shape how GenAI is being adopted - or resisted - across the academic community.

02

EXECUTIVE SUMMARY

| GENERATIVE ARTIFICIAL INTELLIGENCE IN ACADEMIA: Between Operational Enthusiasm and Intellectual Scepticism

What Actually Drives AI Adoption?

The narrative of AI's rapid conquest of academia conceals a significant oversimplification. The adoption of generative AI (GenAI) tools in research environments does not stem from technological herd mentality or social pressure - empirical evidence clearly demonstrates that normative and environmental factors play a marginal role in this process. The decision to reach for such tools is distinctly rational and instrumental: researchers adopt AI if, and only if, they perceive concrete added value for their own work.

Quantitative research findings point to two direct predictors of GenAI usage intention: **perceived usefulness** and **perceived compatibility** with one's existing working style and research rhythm. In other words, a researcher asks above all: "Does this tool solve my specific problems?" and "Does it fit the way I already work?" Both questions must be answered affirmatively before sustained adoption takes place.

A particularly important mediating role is played by **ease of use**. Interface intuitiveness is not a value in itself - it acts as a catalyst that shortens the path from first contact with a tool to recognising its practical utility in everyday research tasks. The lower the cognitive cost of learning the system, the faster a researcher can assess its genuine potential.

A Tool, Not a Replacement: The Application Map

Qualitative research paints a coherent picture of domains where AI finds an ideal fit with the needs of the academic community. The dominant model is treating GenAI as a **high-quality administrative assistant** - a tool that takes over repetitive, structured, and time-consuming activities: preparing grant applications, project reports, literature reviews, and preliminary analysis of large datasets. This frees up the researcher's cognitive resources for those stages of scientific work that require unique competencies: critical thinking, creative synthesis, and deep subject-matter expertise.

One of the most significant and systemically important support mechanisms is the **democratisation of access to global science**. GenAI tools effectively lower the language barrier for researchers whose first language is not English. The ability to efficiently draft, stylistically refine, and adapt manuscripts to the requirements of prestigious international journals allows these scholars to compete on equal terms in the global publication market - a privilege that had previously been available only to a select few.

In the conceptual phase, AI takes on the role of an **intellectual sparring partner**: a tool that supports the organisation of ideas, the testing of working hypotheses, and the exploration of preliminary research concepts. This application is, however, subject to an explicit condition: final substantive verification, assessment of relevance, and responsibility for conclusions must remain unequivocally with the human researcher. AI inspires and organises - it does not decide.

The Anatomy of Distrust: Barriers and Non-Negotiable Limits

Despite declared willingness to use AI, the level of trust in this technology within academia remains low. The explanation for this apparent paradox lies in the specific nature of the scientific ethos. **Hallucinations** - the phenomenon whereby language models generate false information delivered with convincing certainty - represent a critical flaw in an environment whose identity is built around the pursuit of objective, reproducible, and verifiable truth. The lack of result reproducibility makes AI a tool that science cannot trust unreflectively.

An equally powerful barrier is the **"black box" problem** and the associated risk of losing control over intellectual property. Researchers reject the use of GenAI for tasks involving unpublished data, preliminary research findings, or manuscript concepts in preparation. The fear of losing copyright and unintentionally disclosing protected information is one of the strongest and most difficult barriers to overcome.

No less significant is the **structural and social dimension**. The automation of analytical tasks that have traditionally served as an apprenticeship for junior researchers - assistants, doctoral students, and undergraduates - threatens to erode the fundamental mentor–apprentice relationship. When AI takes over laborious yet formatively critical activities, positions and opportunities to acquire practical research competencies disappear, and without those foundations it becomes impossible to build a solid professional career in academia.

Finally, a clear **red line of empathy and ethics** is drawn: tasks requiring moral judgement, resolution of interpersonal conflicts, assessment of student work, and individual mentoring are widely regarded as inherently human domains. Automation in these areas is not perceived as support, but as a degradation of the process and a diffusion of responsibility. According to the respondents, the quality of a relationship and the integrity of an assessment cannot be uploaded into an algorithm.

Leaders vs. Supervisors: The Paradox of Responsibility

A particularly compelling dimension of the research is the comparison of attitudes between two groups: **institutional leaders** (those in managerial positions) and **academic supervisors** without such functions. Leaders tend to demonstrate stronger intentions to adopt AI - overwhelmed by administrative duties, resource management, and grant project coordination, they see in GenAI enormous opportunities to optimise managerial processes and reduce bureaucratic burden. The paradox emerges, however, the moment the conversation shifts to tasks requiring abstract thinking, critical judgement, and adherence to ethical standards. Those same enthusiastic leaders then set the **hardest limits** and express the strongest resistance to AI - considerably more radical than that of typical supervisors. People managing academic institutions, while open to operational improvements, simultaneously demonstrate the deepest awareness of what in science is irreplaceable. This paradox of responsibility is psychologically coherent: the broader the systemic perspective, the clearer the distinction between what can be delegated and what constitutes the unique value of human intellect and academic ethos.

Strategic Implications and Recommendations

The research findings translate into concrete guidance for institutional decision-makers. Above all, there is a clear need to **move away from generic training** describing technical aspects of gen AI (i.e., how language models work), towards programmes focused on integrating AI into precisely defined research tasks like optimising literature reviews, drafting grant applications, or preprocessing data. A contextual, task-oriented approach to technology education consistently yields better outcomes than general awareness training.

The **risk of access inequality** demands urgent attention. The real prospect of dividing the academic community into researchers equipped with advanced paid tools and those reliant on limited free versions poses a genuine threat to the principle of equal opportunity in science. Universities and research institutions should develop models for **institutional, secure, and auditable access** to advanced AI systems, ensuring that the quality of a researcher's tools is not determined by the depth of their personal budget.

Finally, the academic community urgently needs **regulatory clarity**. The absence of coherent, transparent legal and ethical frameworks generates uncertainty that fosters the emergence of informal prohibitions and restrictions - often arbitrary and disproportionately harmful to junior members of the academic community. Clear guidelines specifying which AI applications are permitted, which require disclosure, and which are unconditionally prohibited are an essential prerequisite for the responsible and equitable deployment of this technology in academia.

Methodological Note: This executive summary is based on a dual-phase research conducted in early 2026. The findings incorporate quantitative data from 136 researchers in Poland, Spain, and Portugal (using Structural Equation Modeling based on an extended Technology Acceptance Model) and qualitative insights from four Focus Group Interviews with academic leaders and supervisors in Poland, Spain, and Portugal.

03

QUALITATIVE STUDY

METHODOLOGY

This chapter presents the findings of a qualitative study conducted through Focus Group Interviews (FGI) with academic researchers. The study aimed to diagnose the barriers, concerns, and perceived threats associated with the integration of Generative Artificial Intelligence (GenAI) tools into the professional practices of scientists and scholars. Data collected capture participants' direct experiences with GenAI technologies, their perceived benefits, the structural and institutional constraints they encounter, and broader reflections on the long-term implications of AI adoption in academic work.

Research Design

The study used a qualitative research design centred on Focus Group Interviews (FGI). FGIs are a well-established method for generating data on attitudes, and perceptions in relation to a shared phenomenon. This format was deemed particularly appropriate given the study's interest in collective sensemaking and the normative dimensions of GenAI adoption within professional communities of practice. The focus group format enables participants to respond to and build upon each other's contributions, generating richer and more contextualised data than individual interviewing alone.

Participants

Participants were recruited from the academic research community. The sample included researchers at varying stages of their careers, from early-career scientists to senior academic staff with substantial institutional experience. This diversity was intentional, as the study sought to capture the differential impact of GenAI adoption across career stages and institutional positions. Recruitment targeted researchers across multiple disciplines to ensure breadth of perspective. A total of 4 in-depth interviews were conducted: 2 in Poland, 1 in Portugal, and 1 in Spain.

The following participants took part in the interviews:
FGI in Poland (Warsaw): 4 academic supervisors and Higher Education leaders
FGI in Poland (Łódź): 8 academic supervisors and Higher Education leaders
FGI in Portugal (Porto): 8 academic supervisors and Higher Education leaders
FGI in Spain (Barcelona): 7 academic supervisors and Higher Education leaders

Data Collection and Analysis

FGI sessions were conducted using a semi-structured interview scenario that addressed participants' awareness of GenAI tools, their patterns of use, their perceptions of risk and benefit, and their views on institutional regulation.
The study was conducted from February 17 to March 6, 2026. The interviews were conducted according to a semi-structured scenario and lasted approximately 1.5 hours. The interviews were conducted in the participants' native languages. Sessions were audio-recorded and transcribed verbatim. The transcripts were subjected to thematic analysis following established qualitative procedures, with themes identified inductively from the data and subsequently organised into a coherent analytical framework.

Ethical Considerations

Participation in the study was voluntary, and informed consent was obtained from all participants prior to data collection. All data were anonymised prior to analysis, and no identifying information is presented in this report. The study was conducted in accordance with applicable ethical guidelines governing research with human participants.

The findings are organised thematically around four principal axes: (1) the transformative effects of GenAI on the academic profession; (2) the perceived advantages and patterns of use among researchers; (3) the barriers and concerns that limit or complicate adoption; and (4) deeper reflective concerns regarding professional identity, equity, and the long-term trajectory of academic knowledge production. Each of these themes is treated in depth in the sections that follow.

QUALITATIVE RESULTS: THE IMPACT AND PERCEPTION OF GENAI IN ACADEMIC WORK

2.1 The Impact of GenAI on the Academic Profession

One of the themes emerging from the FGI sessions was the perception that GenAI is reshaping the conditions of academic work - not as a distant future prospect, but as an ongoing, observable transformation. Participants described a profession in flux, in which established norms, career pathways, and standards are being destabilised. This perception was shared across career stages, though the specific dimensions of concern varied between junior and senior researchers.

2.1.1 The Publication Landscape

One of the most immediate salient effects identified by participants was the dramatic expansion in the volume of submissions of research papers to academic journals and conferences. Researchers reported that the reduced effort required to produce draft manuscripts when supported by GenAI has led to an inflation of submission numbers that the peer review system is struggling to absorb. As a consequence, the competitive threshold for publication appears to have risen, making it increasingly difficult for any individual researcher to secure acceptance, even when the quality of their work is high.

This phenomenon introduces a structural paradox: the same tool that enables greater productivity at the individual level may, at the systemic level, produce conditions of heightened scarcity and competition that ultimately disadvantage all participants.

2.1.2 Integrity of Peer Review

A related concern, reported by several participants, pertains to the integrity of the peer review process itself. Researchers described encountering reviewer comments that appeared to contain factually inaccurate or unverifiable claims - claims they attributed to reviewers' use of GenAI tools to assist in the production of their assessments. This phenomenon, in which AI-generated misinformation infiltrates the scholarly evaluation pipeline, poses a direct threat to the quality control mechanisms on which scientific publishing depends.

2.1.3 Erosion of Junior Positions and Apprenticeship Models

Participants observed a beginning of structural shift in the composition of research teams, specifically the disappearance of junior research positions. Tasks that were previously assigned to research assistants and early-career academics - such as data cleaning, coding, qualitative data analysis, and basic programming - are increasingly being performed by GenAI tools. While this shift may appear to represent a gain in efficiency, participants highlighted a significant attendant loss: the erosion of the traditional apprenticeship model through which junior researchers develop their methodological competencies under the supervision of experienced scholars.

This master-apprentice relationship has historically served as the primary mechanism for the intergenerational transmission of research craft knowledge - tacit, embodied forms of expertise that are not easily captured in formal curricula. The substitution of junior researchers by AI tools thus represents not merely an economic or structural adjustment, but a potential rupture in the continuity of academic disciplines.

2.1.4 Devaluation of Accumulated Experience

Several participants expressed concern that the emergence of GenAI threatens to devalue the accumulated expertise of experienced researchers. The perceived risk is that a less experienced researcher, when equipped with powerful AI tools, may be able to produce outputs of comparable apparent quality to those of a seasoned scholar. This prospective levelling of the productive playing field challenges established hierarchies of grounded authority within academic institutions and may undermine the perceived value of long-term investment in scholarly training and academic development.

2.1.5 Changing Student Attitudes Toward Intellectual Labour

A concern noted by several participants related to a discernible shift in the attitudes of some students toward the value of intellectual effort. Participants reported encountering students who appeared to view GenAI as a legitimate substitute for independent cognitive work, with a corresponding indifference to the quality or originality of their outputs. While this phenomenon was acknowledged to be currently limited in scope, participants expressed concern that it may represent the early stages of a broader cultural shift in attitudes toward learning and scholarship - with potentially significant consequences for educational outcomes and the cultivation of research competencies.

2.1.6 The Acceleration Imperative

A final structural concern relates to what might be termed the 'acceleration imperative'. The productivity gains enabled by GenAI create the expectation - at both institutional and individual levels - that all researchers will keep pace with an accelerating rhythm of output. Those who are either unable or unwilling to incorporate GenAI into their workflows risk being perceived as insufficiently productive, regardless of the intrinsic quality of their work. This dynamic may intensify existing pressures in an already demanding professional environment, potentially exacerbating issues of researcher wellbeing, work-life balance, and burnout.

2.2 Perceived Advantages and Patterns of Use

Despite the concerns catalogued above, participants also identified a range of significant benefits associated with GenAI tools, and many reported incorporating these tools into their professional practice in various ways. This ambivalence - acknowledging utility while maintaining critical distance - was a characteristic stance across the participant group.

2.2.1 Productivity and Efficiency

The most universally acknowledged benefit was an increase in the speed of completing routine and time-intensive tasks. Participants reported using GenAI to accelerate administrative work, including the drafting of reports, grant applications, and institutional forms. The reduction in time spent on such activities was perceived as freeing cognitive resources for more substantive intellectual work - a framing that positions GenAI as a tool for the optimisation of scholarly attention rather than a replacement for scholarly thought.

2.2.2 Idea Development and Critical Dialogue

Several participants described using GenAI tools as a form of intellectual interlocutor - a resource for testing ideas, soliciting alternative perspectives, and refining arguments. This use case positions GenAI not as a replacement for human thought but as a supplementary dialogue partner capable of providing structured feedback and constructive challenge. Participants found this function particularly valuable in the early stages of research design and manuscript preparation, describing interactions with AI tools that functioned analogously to conversations with a knowledgeable but uncritical colleague.

2.2.3 Language Accessibility and Publication Equity

A benefit of particular note was the reported elimination of what participants described as the 'native speaker barrier' in international scholarly publishing. Researchers for whom English is not a first language reported that GenAI tools had substantially improved the accessibility of English-language publication venues by assisting in the production of linguistically polished manuscripts. This democratising effect represents a meaningful reduction in one of the most persistent structural inequities in global academic publishing.

2.2.4 Idea Generation and Literature Review

Participants also reported using GenAI to support brainstorming and literature review processes. In the former case, tools were used to generate candidate ideas, research questions, or conceptual frameworks that could then be evaluated and refined by the researcher. In the latter, GenAI was used to assist in mapping the existing state of knowledge in a given field, although this application was accompanied by significant caveats regarding reliability, as discussed further in Section 2.3.

2.3 Barriers and Concerns

The barriers and concerns articulated by participants were multidimensional and interconnected. They span technical, institutional, professional, and ethical domains, and together paint a picture of a research community that is cautiously engaging with a technology it does not fully trust, understand, or control. The following subsections address each principal barrier in turn.

2.3.1 Epistemic Unreliability and Hallucination

The most consistently and forcefully articulated concern pertained to the unreliability of GenAI outputs. Participants reported direct personal experience of AI 'hallucinations' - the generation of confident-sounding but factually inaccurate or entirely fabricated information. For a community whose professional identity is organised around the pursuit of reliable knowledge, this characteristic is a fundamental disqualifier for many potential use cases.

Compounding this concern is the challenge of distinguishing reliable from unreliable AI outputs. Participants noted that GenAI-generated content is often linguistically and rhetorically polished, making it difficult to identify errors without independent verification - a process that may negate much of the efficiency gain the tool is supposed to provide. This observation points to a fundamental tension in the deployment of GenAI in research contexts: the tool's greatest strength, its fluency, is simultaneously the quality that makes its errors most dangerous.

2.3.2 Instability and Non-Reproducibility

Participants raised significant concerns about the instability of GenAI tools over time and across sessions. Several noted that the same prompt may yield substantially different outputs on different occasions, and that tool performance can degrade markedly once token or session limits are exceeded. Additionally, researchers noted that underlying model updates are implemented without user notification, meaning that a tool's behaviour may change in ways that are invisible to the user. These characteristics are fundamentally incompatible with the norms of scientific reproducibility, which require that methods and results be stable and verifiable across time and contexts.

2.3.3 Data Privacy and the 'Black Box' Problem

A significant concern relates to the privacy implications of inputting sensitive research data into GenAI systems. Participants described AI platforms as 'black boxes': once data - including raw datasets, analytical outputs, or manuscript drafts - are uploaded, users have no visibility into how that information is stored, processed, or potentially reused. This concern is particularly acute in research contexts involving confidential or personally identifiable data, and may render GenAI tools incompatible with the ethical and legal requirements governing data protection in academic research environments.

2.3.4 Formal and Informal Institutional Prohibitions

Several participants reported that their institutions had implemented prohibitions - both formal and informal - on the use of GenAI tools in research and teaching contexts. Formal prohibitions, where they existed, were embedded in institutional regulations or codes of conduct. Informal prohibitions - often more powerful in practice - took the form of discouraging signals from senior colleagues or supervisors, whose authority within strongly hierarchical academic cultures can effectively suppress the adoption of new practices among junior researchers even in the absence of explicit rules.
The chilling effect of informal norms on early-career researchers is of particular concern, given that junior academics are simultaneously among the most likely adopters of new technologies and the most professionally vulnerable members of the academic community. An informal discouragement from a senior supervisor may have the practical force of an institutional prohibition for a researcher who depends on that supervisor's advocacy for their career progression.

2.3.5 Regulatory Ambiguity

Paradoxically, many institutions had not yet developed clear regulatory frameworks governing GenAI use, leaving researchers uncertain about what was permitted, prohibited, or permissible under specific conditions. This ambiguity was experienced as a source of anxiety by the majority of participants, who expressed a desire for clear and consistent institutional guidance. A small minority, however, reported experiencing the absence of formal rules as a permissive environment that enabled free experimentation. This minority response is notable: it illustrates how the same structural condition - regulatory vacuum - can produce opposite behavioural responses depending on an individual's risk tolerance and professional positioning within the institution.

2.3.6 Knowledge Gaps Regarding Available Tools

Participants reported significant uncertainty about the landscape of available GenAI tools, their respective functionalities, and their potential applications in research contexts. Many felt inadequately equipped to make informed decisions about which tools to adopt, for which purposes, and with what safeguards. As one participant articulated, researchers need to understand what AI is in order to function as effective guides for their students. This sentiment captures a broader pedagogical crisis: faculty members responsible for guiding students through an AI-transformed educational landscape feel underprepared for that role.

2.3.7 Lack of Institutional Support and Subscription Costs

A structural barrier of considerable practical significance is the absence of institutional support for accessing premium GenAI tools. Many of the most capable and reliable GenAI platforms require paid subscriptions that represent a non-trivial personal expense for academic researchers. Without institutional provision of access, the adoption of these tools may be effectively constrained by financial means, introducing a new dimension of inequality into the research environment. Participants suggested that institutional subscription arrangements would substantially facilitate equitable and informed adoption of these technologies across the research community.

2.4 Reflective Concerns: Identity, Equity, and the Future of Scholarly Work

Beyond the pragmatic concerns discussed above, participants engaged in more fundamental reflective questioning about the long-term implications of GenAI for the nature of academic work, professional identity, and academic equity. These reflections, while more speculative in character, are no less significant for policy and institutional planning.

2.4.1 Cognitive Sovereignty and Professional Identity

Several participants described a form of deliberate cognitive self-monitoring in relation to their use of GenAI - an active consideration of which intellectual tasks they wished to retain for themselves and which they were prepared to delegate to AI. This disposition reflects a concern for what might be termed 'cognitive sovereignty': the preservation of autonomous intellectual agency in a context where the boundaries between human and machine cognition are becoming increasingly fluid.

A specific instance of this reflective concern involved the question of whether researchers should modify their communicative behaviour to optimise GenAI performance - for example, by adopting a more directive or demanding tone with AI systems if this has been reported to yield better outputs. This scenario encapsulates a broader tension: to what extent should researchers adapt their professional and personal habits to the requirements of AI systems, and at what point does such adaptation constitute a compromise of professional integrity or personal identity?

2.4.2 Accessibility of Intellectual Production and Epistemic Inflation

A concern of particular salience for the academic community pertains to what participants described as the democratisation - and potential debasement - of intellectual production. When powerful AI tools enable individuals without specialised expertise to produce outputs that superficially resemble high-quality scholarly work, the epistemic currency of academic publication may be devalued. This concern is not merely elitist or self-protective; it reflects a genuine anxiety about the capacity of academic institutions to maintain meaningful quality standards when the production of plausible-sounding scholarship becomes widely accessible to those who lack the disciplinary competencies to produce original contributions independently.

2.4.3 The Long-Term Viability of the Intellectual Vocation

Some participants raised the speculative but urgent question of whether a world in which machine-generated text is indistinguishable from human-produced analysis might ultimately render the figure of the intellectual - the scholar who produces knowledge through sustained, effortful, rigorous inquiry - economically marginal or socially superfluous. While this scenario remains prospective, the fact that it is being articulated by working researchers reflects the depth of the uncertainty that GenAI has introduced into the academic imaginary. It invites serious reflection on the social and institutional conditions that sustain the value attributed to human intellectual labour.

2.4.4 Emerging Inequities Between Adopters of Premium and Free Tools

A final concern of structural significance relates to the potential emergence of a two-tier academic community, stratified by access to premium GenAI capabilities. Researchers who can afford - or whose institutions provide - access to advanced AI tools may enjoy substantially enhanced productivity and output quality relative to those reliant on free or lower-capability alternatives. These dynamic risks replicating and amplifying existing inequalities in academic research, between well-resourced and resource-constrained institutions.

04

QUANTITATIVE STUDY

METHODOLOGY

Research aim

This chapter presents the findings of a quantitative study conducted with academic researchers. The aim of this study is to identify drivers and barriers to the adoption of Generative Artificial Intelligence (GenAI) among higher education professionals in the context of research and teaching activities.

Research design

The analysis is conducted from two complementary perspectives. First, drivers and barriers are examined through determinants of technology use derived from the extended Technology Acceptance Model (Sakib et al., 2025). Second, these drivers & barriers are interpreted in relation to key domains of researcher competence as defined in the 'The European Competence Framework for Researchers' (OPUS, 2025), allowing the study to situate GenAI adoption within broader professional practices and capability structures.

Sample and participants

Data were collected using the CAWI (Computer-Assisted Web Interviewing) technique. The final sample consisted of N = 136 respondents; however, four participants did not complete all survey items related to the measurement of Extended Technology Acceptance Model constructs. The sample included 44 higher education leaders, 77 supervisors who were not in leadership roles, and 15 researchers representing other professional categories. Respondents were recruited from Poland, Spain, and Portugal. Data collection was conducted between January 27 and April 6, 2026.

In terms of research fields, the sample was dominated by respondents representing Management, Business, and Entrepreneurship (24%), followed by Finance, Accounting, and Tax (18%) and Economics (15%). Other fields included IT, Computer Science, HCI, and Machine Learning (7%), Marketing and Social Media (5%), Law (4%), Sociology (4%), Psychology (3%), and Mathematics and Statistics (2%). The remaining disciplines were represented by smaller shares (1–2% each), including Engineering, Neuroscience, Operational Research, Transport and Logistics, Tourism, Cultural Studies, Journalism and Communication, Biology and Biotechnology, Project Management, Human Resource Management, Consumer Behavior, as well as other fields (3%).

Ethical considerations

Participation in the study was voluntary. All data were anonymised prior to analysis, and no identifying information is presented in this report. The data were analysed in aggregated form. The study was conducted in accordance with applicable ethical guidelines governing research with human participants.

FRAMEWORK FOR UNDERSTNDING GENERATIVE AI ADOPTION

3.1 A technology acceptance perspective

Effective strategies to support generative AI adoption should focus on users' beliefs and perceptions, as these cognitive factors can be shaped through organizational interventions, communication, and training. A well-established framework for analyzing technology adoption is the Technology Acceptance Model (TAM) (Davis, 1989), which identifies two core drivers of technology use: perceived usefulness and perceived ease of use.

More recent research extends TAM by incorporating additional determinants relevant for emerging technologies. In the present study, we test an extended model that includes factors proposed by (Sakib et al., 2025), allowing for a broader understanding of generative AI adoption. Identifying the relative importance of these factors enables the detection of key drivers that shape the intention to use generative AI, particularly within the context of higher education professionals.

3.2 Identifying key determinants of generative AI solutions adoption

To identify the key determinants of generative AI adoption, the model builds on the Technology Acceptance Model (Davis, 1989) and its extensions, particularly the framework proposed by Sakib et al. (2025). It assumes that behavioral intention to use generative AI is directly influenced by a set of key drivers, including perceived usefulness, perceived ease of use, compatibility, trust, perceived cost, enjoyment, facilitating conditions, and social influence. All of these factors are included simultaneously to assess their relative contribution to adoption, allowing for the identification of those that exert a unique effect beyond shared variance with other constructs.

In addition to direct effects, the model incorporates selected mediating mechanisms. Specifically, social influence is modeled as a mediator, capturing how perceived compatibility and trust may translate into stronger adoption intentions through external opinions, norms, and social reinforcement. Similarly, facilitating conditions are treated as a mediator, reflecting how perceived ease of use may enhance adoption indirectly by strengthening users' perception of available support, resources, and enabling environment.

At the same time, the present study extends the model proposed by Sakib et al. (2025) by explicitly incorporating the core TAM pathway, which was not specified in their framework. In particular, we model perceived ease of use as an antecedent of perceived usefulness, allowing us to capture the fundamental cognitive mechanism through which usability translates into adoption. Figure 1 presents the conceptual model tested in this study.

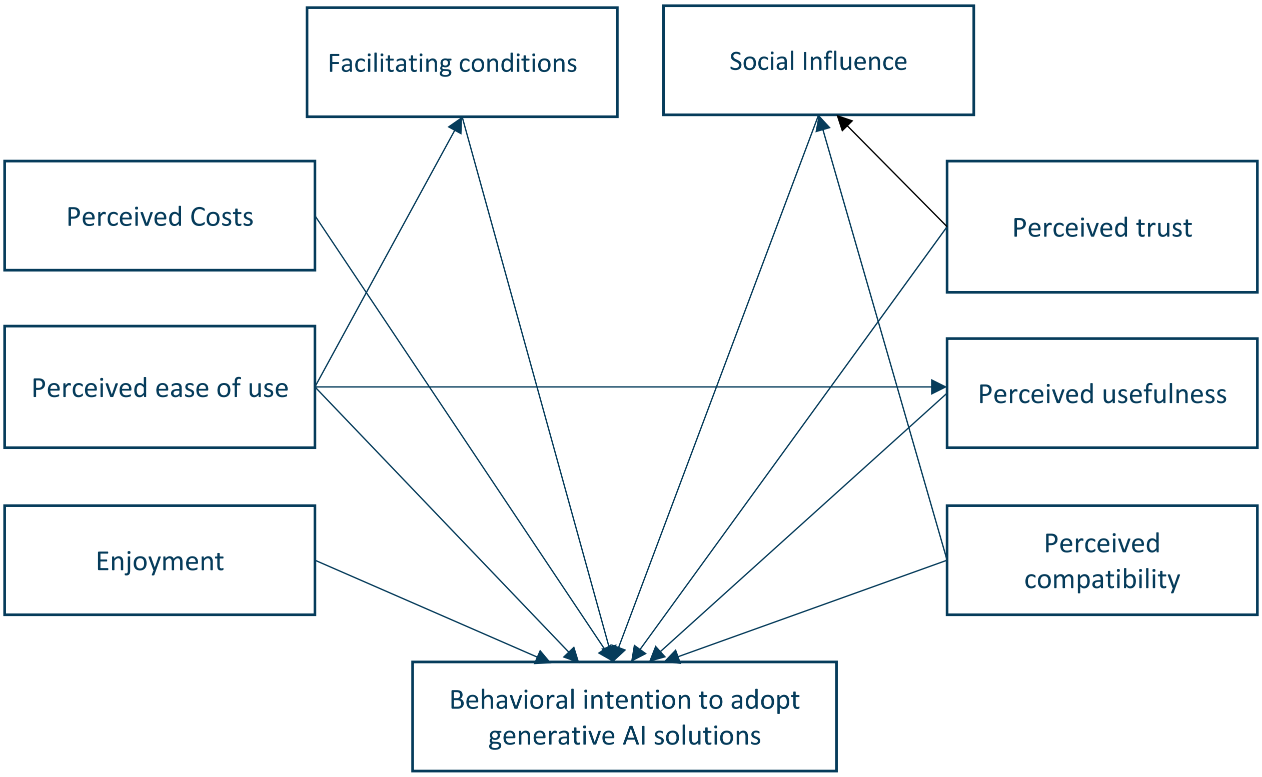

Figure 1. Conceptual framework of the extended Technology Acceptance Model, adapted from Sakib et al. (2025) and grounded in the original TAM proposed by Davis (1989).

3.3 Measurement

The constructs of the extended Technology Acceptance Model were measured using previously validated scales adapted from prior studies. The following measures were included:

Construct	Source
Behavioral Intention to adopt Generative AI solutions	(van Bussel et al., 2022)
Perceived usefulness / Perceived ease of use / Social influence / Enjoyment / Facilitating Conditions	(Venkatesh et al., 2012)
Perceived Cost	(Tsu Wei et al., 2009)
Perceived Compatibility	(Cheng, 2015)
Perceived trust	(Chandra et al., 2010)

Behavioral intention reflects the user's willingness to use generative AI solutions in the future. It is considered the proximal predictor of actual behavior.
Perceived usefulness refers to the extent to which individuals believe that using generative AI enhances their effectiveness in achieving important goals, increases productivity, and enables them to complete tasks more efficiently in their daily activities.
Perceived ease of use captures the degree to which generative AI is perceived as easy to learn, intuitive, and effortless to operate, including the clarity of interaction and the ability to quickly develop proficiency in using the system.

Social influence reflects the extent to which individuals perceive that important others-such as colleagues, supervisors, or valued peers-expect or encourage them to use generative AI solutions, thereby shaping their adoption decisions.
Trust refers to the individual's confidence in the reliability, security, and overall trustworthiness of generative AI systems, including the belief that such solutions can perform tasks accurately and can be safely relied upon.
Enjoyment captures the degree to which individuals experience pleasure, fun, and entertainment when using generative AI, reflecting intrinsic motivation independent of performance-related benefits.
Perceived costs refer to the extent to which individuals perceive financial burden associated with generative AI, including access fees, subscription costs, and the overall expense of using such solutions.
Facilitating conditions reflect the extent to which individuals perceive that they have the necessary resources, knowledge, and support to use generative AI, including access to help and compatibility with existing technologies.
Finally, **compatibilit**y refers to the extent to which generative AI solutions are perceived as aligned with users' existing work practices, preferences, and working style, indicating how well the technology fits into their daily professional routines.

3.3.1 Data preparation and measurement validation

Prior to testing the structural relationships, the measurement model was evaluated using confirmatory factor analysis (CFA). The results indicate that the proposed factor structure demonstrates good overall fit and satisfactory psychometric properties.

During measurement model validation, two items from the Facilitating conditions scale were removed due to low factor loadings, which improved construct reliability and overall model fit. The removed items are highlighted in red in Appendix 1. After removing these items, standardized factor loadings ranged from .65 to .95. Three items exhibited slightly lower loadings, falling below the recommended threshold of .70 (Hair et al., 2019); however, they were retained due to their theoretical relevance and acceptable contribution to the constructs, indicating overall satisfactory indicator reliability.

The CFA model showed acceptable fit to the data: $\chi^2(314) = 533$, $p < .001$; $\chi^2/df = 1.70$; CFI = .938; TLI = .925; RMSEA = .073 (90% CI [.062, .083]); SRMR = .048. All indices met commonly recommended thresholds for acceptable model fit (Hu & Bentler, 1999; Kline, 2016), indicating a well-fitting measurement model.

Internal consistency was supported by Cronbach's alpha values ranging from .75 to .96 and composite reliability (CR) values between .76 and .96, both exceeding the recommended threshold of .70 (Hair et al., 2019). Convergent validity was confirmed, as average variance extracted (AVE) values ranged from .60 to .89, surpassing the .50 criterion (Hair et al., 2019).

Discriminant validity was assessed using the heterotrait–monotrait ratio (HTMT), with values ranging from .033 to .923. A slight exceedance of the recommended threshold of .90 (Henseler et al., 2015) was observed only for the relationship between perceived usefulness and behavioral intention; however, this is considered acceptable given their strong conceptual relatedness within the Technology Acceptance Model (Davis, 1989).

Prior to structural model estimation, correlations between latent constructs were examined to assess preliminary relationships and inform model specification (Figure 2). In addition to direct relationships, the assumptions underlying the proposed mediating mechanisms were also examined at the correlation level to assess whether the prerequisite associations for indirect effects were present. The correlation matrix revealed a coherent and theoretically consistent structure among the analyzed variables.

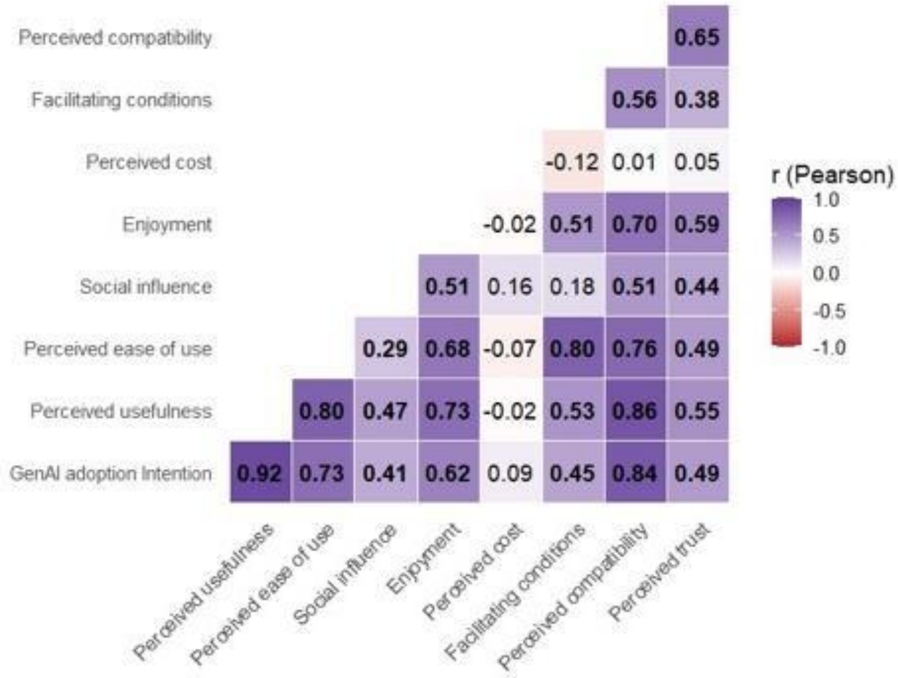

Figure 2. Relationships between constructs (latent variables) in the proposed research model.

Regarding the two core constructs of the Technology Acceptance Model, the strongest relationship was observed between behavioral intention to adopt generative AI solutions and perceived usefulness (r = .92). Perceived ease of use was also strongly related to perceived usefulness (r = .80) and showed a substantial association with behavioral intention to adopt generative AI solutions (r = .73), supporting the expected relationships within the TAM framework.

Within the extended model, several associations were identified that provide support for the proposed mediating mechanisms. In particular, perceived ease of use was strongly correlated with facilitating conditions (r = .80), which underpins its indirect pathway to adoption. Compatibility was moderately associated with social influence (r = .51), while trust demonstrated a weaker but still meaningful relationship with social influence (r = .44), supporting the role of social influence as a mediator in translating these perceptions into adoption intentions.

In contrast, perceived cost did not exhibit meaningful correlations with behavioral intention to adopt generative AI solutions (r = .09) or with other constructs in the model (r ranging from −.12 to .16). This lack of association indicates that perceived cost is not integrated within the broader network of relationships underlying generative AI adoption. Given this pattern, as well as considerations related to model complexity and sample size, perceived cost was excluded from further analyses and not retained as a determinant of generative AI adoption.

Overall, presented relationships in Figure 2 indicate that the variables included in the model form a coherent structure that supports both direct and indirect pathways contributing to the uptake of generative AI solutions. Before proceeding to the structural model, descriptive analyses were conducted to examine the levels of constructs reflecting the potential for generative AI adoption across professional groups.

3.3.2 Mean levels of adoption constructs across HE professional groups

Latent constructs do not have directly observable values; therefore, mean scores were calculated as averages of the items comprising each construct to enable comparison across groups. Figure 3 presents the mean levels of constructs across the analysed groups of higher education professionals.

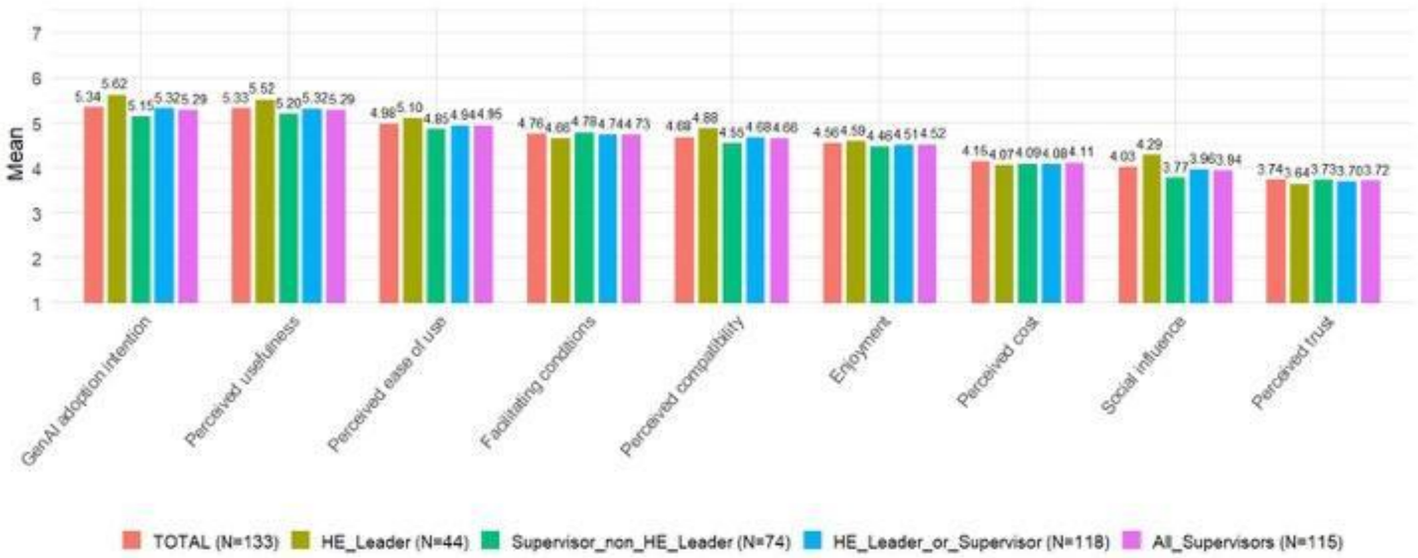

Figure 3. Mean levels of adoption constructs across HE professional groups.

Overall, the results indicate a generally positive, yet moderate orientation toward generative AI adoption. Behavioural intention and perceived usefulness show the highest values across all groups, suggesting that respondents recognize the potential benefits of generative AI in their professional activities.

Across most constructs, HE leaders tend to report slightly higher values compared to supervisors and non-leaders. Although these differences were not statistically significant, a consistent trend can be observed, particularly for behavioural intention and social influence. Specifically, HE leaders reported higher behavioural intention ($M = 5.62$, $SD = 1.29$) than supervisors non-HE leaders ($M = 5.15$, $SD = 1.38$; Welch's $t(95.43) = 1.88$, $p = .064$). A similar pattern was found for social influence, with HE leaders scoring higher ($M = 4.29$, $SD = 1.50$) than supervisors non-HE leaders ($M = 3.77$, $SD = 1.42$; Welch's $t(86.89) = 1.85$, $p = .068$).

At the same time, clear differences emerge in the relative strength of individual dimensions. Trust represents the lowest observed mean ($M \approx 3.74$), which is approximately 1.6 scale points lower than behavioural intention. This suggests a substantial gap between willingness to use generative AI and confidence in its reliability and safety. Similarly, social influence remains relatively weak ($M \approx 4.03$), approximately 1.3 points below behavioural intention, indicating that external pressure or normative expectations are limited in this context.

STRUCTURAL MODEL RESULTS

3.4 Key determinants of generative AI adoption

An a priori power analysis was conducted using G*Power (Faul et al., 2007) for a linear multiple regression model. Assuming a medium effect size ($f^2 = 0.15$), $\alpha = .05$, and desired power of .90, the analysis indicated a required minimum sample size of N = 136 for a model with eight predictors. However, because perceived cost was excluded from the final model due to its negligible correlations with behavioral intention and the remaining constructs, the final structural model included seven predictors, for which the required minimum sample size was N = 130. Two cases exceeding the critical Mahalanobis distance threshold were identified as multivariate outliers and subsequently removed from the dataset. As a result, the final analyses were conducted on a sample of N = 131 cases, which was sufficient for estimating the proposed model. Although the power analysis was based on a multiple regression framework, it provides a conservative approximation for structural equation modeling, as SEM estimates regression relationships among latent variables.

The structural model demonstrated an acceptable fit to the data, with CFI = .921, TLI = .910, RMSEA = .081 (90% CI [.071, .091]), and SRMR = .078.The chi-square to degrees of freedom ratio was $\chi^2/df = 1.86$ ($\chi^2(329) = 612.94$, $p < .001$). The model explained a substantial proportion of variance in behavioral intention to adopt generative AI solutions ($R^2 = .869$), indicating high explanatory power.

The analysis of direct effects revealed that behavioral intention to adopt generative AI solutions is driven by two significant predictors: **perceived usefulness** ($\beta = .627$, $p = .0009$) and **perceived compatibility** ($\beta = .554$, $p = .003$). In contrast, no significant direct effects on behavioral intention were observed for perceived ease of use, facilitating conditions, enjoyment, trust, or social influence, indicating that these variables do not independently explain adoption when considered simultaneously.

The analysis further revealed several significant indirect pathways. Consistent with the original Technology Acceptance Model (Davis, 1989), **perceived ease of use** significantly influenced perceived usefulness ($\beta = .817$, $p < .001$). In addition, perceived ease of use also had a strong and significant effect on facilitating conditions ($\beta = .814$, $p < .001$), indicating that users who perceive generative AI solutions as easy to use are more likely to perceive the availability of resources, support, and enabling conditions. Although perceived ease of use did not exhibit a significant direct effect on behavioral intention, its indirect effect was substantial, operating through perceived usefulness. The estimated **total effect of perceived ease of use** on behavioral intention was approximately $\beta = .51$, indicating a strong indirect influence.

Furthermore, perceived compatibility significantly influenced social influence ($\beta = .337$, $p = .019$), suggesting that when generative AI solutions are perceived as aligned with users' work practices, they are more likely to be socially reinforced within professional environments. However, social influence itself did not have a significant direct effect on behavioral intention, which limits its role as an effective mediator in the model. Similarly, the effect of trust on social influence was positive but not statistically significant ($\beta = .247$, $p = .0946$), indicating only partial support for this pathway.

Overall, the results provide strong support for the core mechanism of the Technology Acceptance Model, in which perceived usefulness acts as the primary driver of behavioral intention, while perceived ease of use operates indirectly by shaping perceived usefulness. Importantly, the absence of a direct effect of ease of use does not imply a lack of importance, but rather reflects its mediated role. At the same time, the findings refine extended TAM approaches (Sakib et al., 2025) by demonstrating that only selected additional constructs retain explanatory power when analyzed simultaneously. In particular, perceived compatibility emerged as a robust independent predictor, whereas other commonly included variables did not show significant direct effects.

3.5 Conclusions

The findings indicate that efforts to increase the adoption of generative AI solutions should focus primarily on enhancing perceived usefulness and perceived compatibility, as these are the only factors that directly drive behavioral intention among higher education professionals. In practice, this means that universities and academic institutions should prioritize demonstrating clear, discipline-relevant performance benefits of generative AI, such as time savings in literature review, support in academic writing, data analysis, and teaching preparation. Communication strategies should therefore be strongly outcome-oriented, emphasizing how these solutions concretely support researchers and educators in achieving their professional goals.

At the same time, the importance of compatibility suggests that adoption is highly dependent on how well generative AI solutions fit into existing academic workflows and professional practices. Institutions should therefore focus on embedding AI solutions into the everyday practices of researchers and educators, rather than presenting them as external or disruptive technologies. This may involve tailoring use cases to specific academic tasks, integrating solutions with commonly used platforms, and aligning them with disciplinary norms. Importantly, compatibility may also extend beyond functional fit to include alignment with professional identity. Positioning generative AI as a legitimate and valuable tool within the identity of a modern researcher-rather than as a shortcut or threat may further strengthen adoption.

Although perceived ease of use does not directly influence adoption, its strong indirect effect highlights its role as a foundational enabler. This has direct implications for training design. Rather than focusing solely on technical instruction, training programs should emphasize applied, task-based learning, where ease of use is demonstrated through concrete academic scenarios (e.g., drafting research outlines, summarizing articles, generating teaching materials). The key objective should be to make explicit how ease of use translates into perceived usefulness in real academic work.

In addition, the descriptive results highlight a moderate level of readiness for generative AI adoption. While higher education professionals show generally positive attitudes and a willingness to use these solutions, this readiness remains far from full engagement at scale. The gap between relatively high behavioral intention and lower levels of trust suggests persistent concerns regarding reliability and safety. At the same time, the relatively weak role of social influence suggests that adoption is driven more by individual evaluation than by normative pressure, reinforcing the importance of personally relevant, use-case-based engagement strategies rather than top-down mandates.

From a practical perspective, effective training strategies for higher education professionals should therefore:

- focus on real academic use cases rather than generic tool demonstrations,
- highlight performance gains in research and teaching tasks,
- embed AI solutions within existing workflows and platforms,
- and support the development of a positive, professional narrative around AI use in academia.

Overall, the results suggest that successful adoption of generative AI in higher education depends less on persuasion or social pressure, and more on enabling individuals to recognize its practical value and integrate it seamlessly into their professional practice and identity.

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Appendix

Appendix 1. Survey items used to measure the extended Technology Acceptance Model.

Construct	Item Code	Item Statement
Intention to adopt GenAI solutions	UAT1_UB1	Assuming generative AI solutions are offered, I would intend to use them.
	UAT1_UB2	I will use generative AI solutions frequently.
	UAT1_UB3	Given that I have access to generative AI solutions, I will use the services.
Perceived usefulness	UAT1_UPU1	I find generative AI solutions useful in my daily life.
	UAT1_UPU2	Using generative AI solutions increases my chances of achieving things that are important to me.
	UAT1_UPU3	Using generative AI solutions helps me accomplish things more quickly.
	UAT1_UPU4	Using generative AI solutions increases my productivity.
Perceived ease of use	UAT1_UEU1	Learning how to use generative AI solutions is easy for me.
	UAT1_UEU2	My interaction with generative AI solutions is clear and understandable.
	UAT1_UEU3	I find generative AI solutions easy to use.
	UAT1_UEU4	It is easy for me to become skillful at using generative AI solutions.
Social Influence	UAT2_USI1	People who are important to me think that I should use generative AI solutions.
	UAT2_USI2	People who influence my work think that I should use generative AI solutions.
	UAT2_USI3	People whose opinions I value prefer that I use generative AI solutions.
Perceived trust	UAT3_UTR1	I would trust generative AI solutions to be reliable.
	UAT3_UTR2	I believe generative AI solutions could provide secure services.
	UAT3_UTR3	I believe generative AI solutions are trustworthy.
Enjoyment	UAT2_UE1	Using generative AI solutions is fun.
	UAT2_UE2	Using generative AI solutions is enjoyable.
	UAT2_UE3	Using generative AI solutions is very entertaining.
Perceived costs	UAT2_UPC1	The access fee for generative AI solutions is expensive for me
	UAT2_UPC2	The subscription fee for generative AI solutions is expensive for me
	UAT2_UPC3	The cost of generative AI solutions is high for me
Facilitating conditions	UAT3_UFC1	I have the resources necessary to use generative AI solutions.
	UAT3_UFC2	I have the knowledge necessary to use generative AI solutions.
	UAT3_UFC3	Generative AI solutions are compatible with other technologies I use.
	UAT3_UFC4	I can get help from others when I have difficulties using generative AI solutions.
Perceived compatibility	UAT3_UCO1	Using generative AI solutions is compatible with most aspects of my work.
	UAT3_UCO2	Using generative AI solutions fits well with the way I like to work.
	UAT3_UCO3	Using generative AI solutions fits my working style.

MATRIX-BASED RESULTS: ADOPTION DRIVERS AND BARRIERS

3.7 Analytical framework and matrix design

In the following pages, we present an analysis of approach and attitudes toward Gen AI across seven areas. We used the research framework defined in the ‘The European Competence Framework for Researchers’ (OPUS, 2025) to contextualize GenAI adoption within researchers’ professional activities, seven competence domains were included as analytical lenses:

Cognitive Abilities – advanced thinking skills used to solve complex problems and generate new knowledge.
Working with Others – collaboration, networking, and inclusive teamwork within research environments.
Self-Management – ability to organize work, maintain productivity, and cope with pressure.
Making an Impact – dissemination of knowledge, teaching, and contributing to society and policy.
Managing Research – planning, coordination, and evaluation of research projects and resources.
Doing Research – core scientific competencies, including methodology, writing, and research integrity.
Managing Research Tools – effective use of data, digital tools, and open science practices

Activities within each area are plotted on a matrix. The X-axis shows the combined percentage of “rather yes” and “definitely yes” responses (Top Two Boxes) obtained in the question about willingness to use Gen AI within particular activity. The Y-axis, on the other hand, shows the sum of the “Rather more pros than cons” and “Definitely more pros than cons” responses (Top two Boxes) to the question about the balance of pros and cons.

Ultimately, four distinct areas can be identified on each map:

High Potential Adoption Drivers:
Upper-right quadrant – high willingness to use and a high percentage of respondents who believe that the use of GenAI in this area has more advantages than disadvantages.

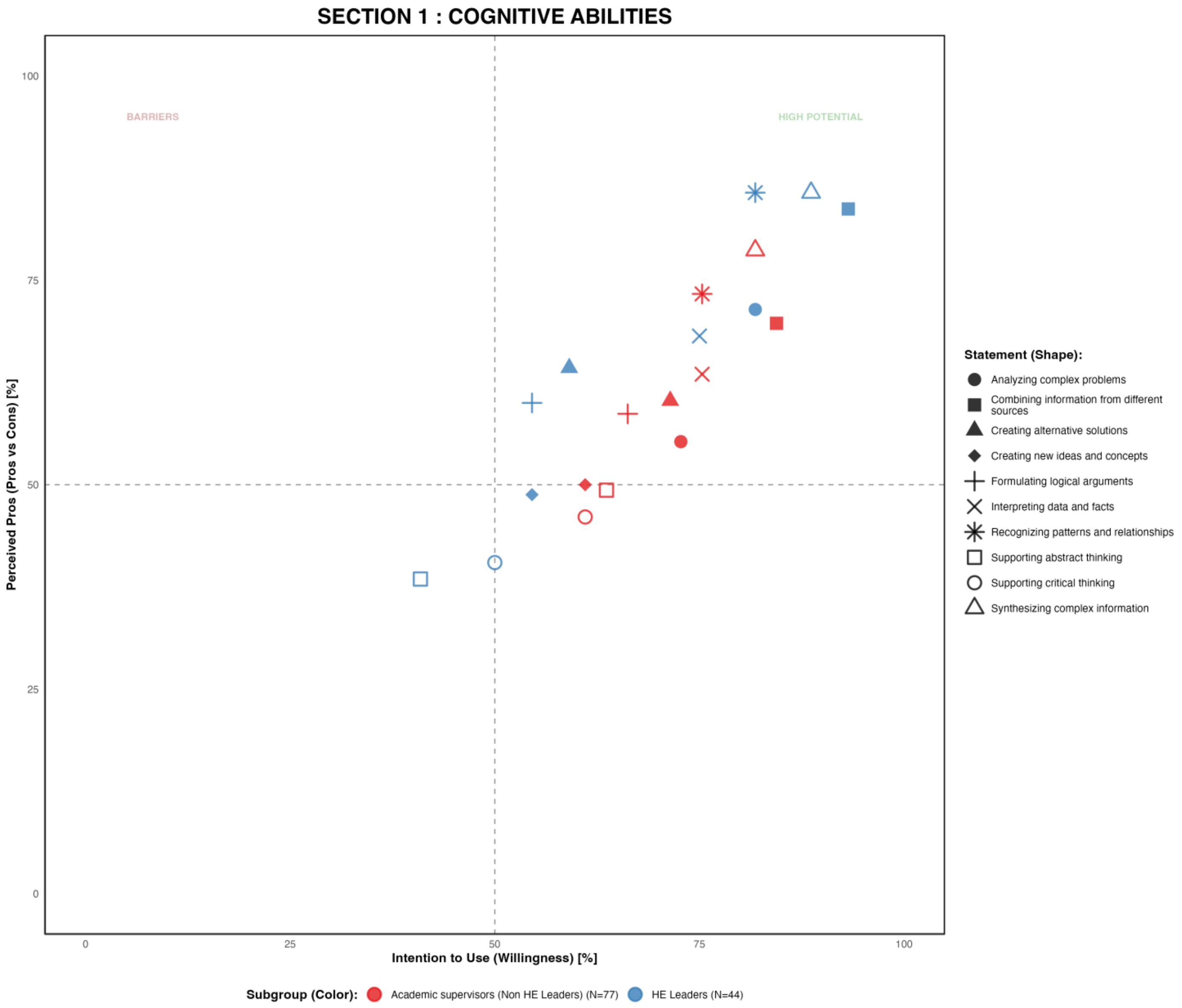
High Impact Barriers:
Lower-left quadrant – low willingness to use and a low percentage of respondents who believe that the use of GenAI in this area has more advantages than disadvantages.

Low Potential Adoption Drivers:
Lower-right quadrant – high willingness to use despite a low percentage of respondents who believe that the use of GenAI in this area has more advantages than disadvantages.

Low Impact Barriers:
Upper-left quadrant – low willingness to use despite a high percentage of respondents believing that the use of GenAI in this area has more advantages than disadvantages.

The results are presented in two separate groups of respondents: Higher Education Leaders (people who manage groups of researchers) n=44; Academic Supervisors who are not Higher Education Leaders n=77.

3.7.1 Cognitive abilities

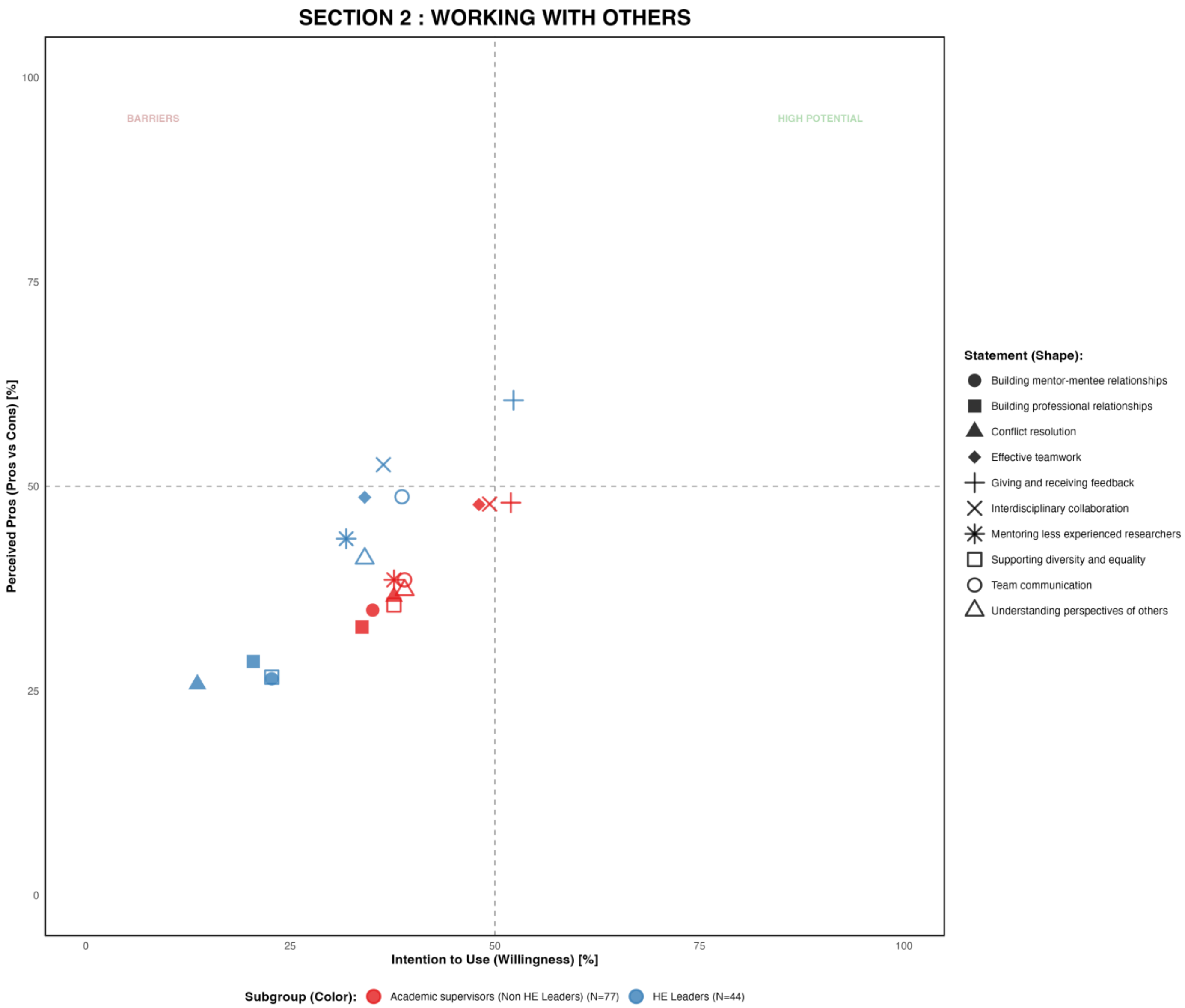


With regard to cognitive abilities, both HE Leaders and Supervisors Non-HE Leaders expressed a broadly positive outlook, with the majority of responses falling within the High Potential quadrant. The strongest endorsement across both groups was recorded for tasks involving the processing and integration of information - most notably combining information from different sources, synthesising complex information, and recognising patterns and relationships - all of which achieved high scores on both willingness and perceived benefit dimensions. This suggests a shared recognition of AI tools as **effective aids in analytically demanding, information-intensive work**.

Conversely, the data reveal a clear and consistent pattern of **scepticism towards tasks of a more conceptual nature**. Supporting abstract thinking and supporting critical thinking received the lowest scores in the matrix, with HE Leaders placing both items below the 50% threshold on both axes - indicating not only limited willingness to use AI tools in these areas, but also doubt as to whether their benefits would outweigh the associated drawbacks. This finding is particularly pronounced among academic leaders, for whom critical and abstract reasoning represent core professional competencies.

Taken together, the results suggest that respondents draw a meaningful distinction between process-oriented cognitive tasks, where AI assistance is broadly welcomed, and higher-order intellectual tasks, where reluctance prevails. This divide should be considered carefully when designing training and implementation strategies within the project.

3.7.2 Working with others

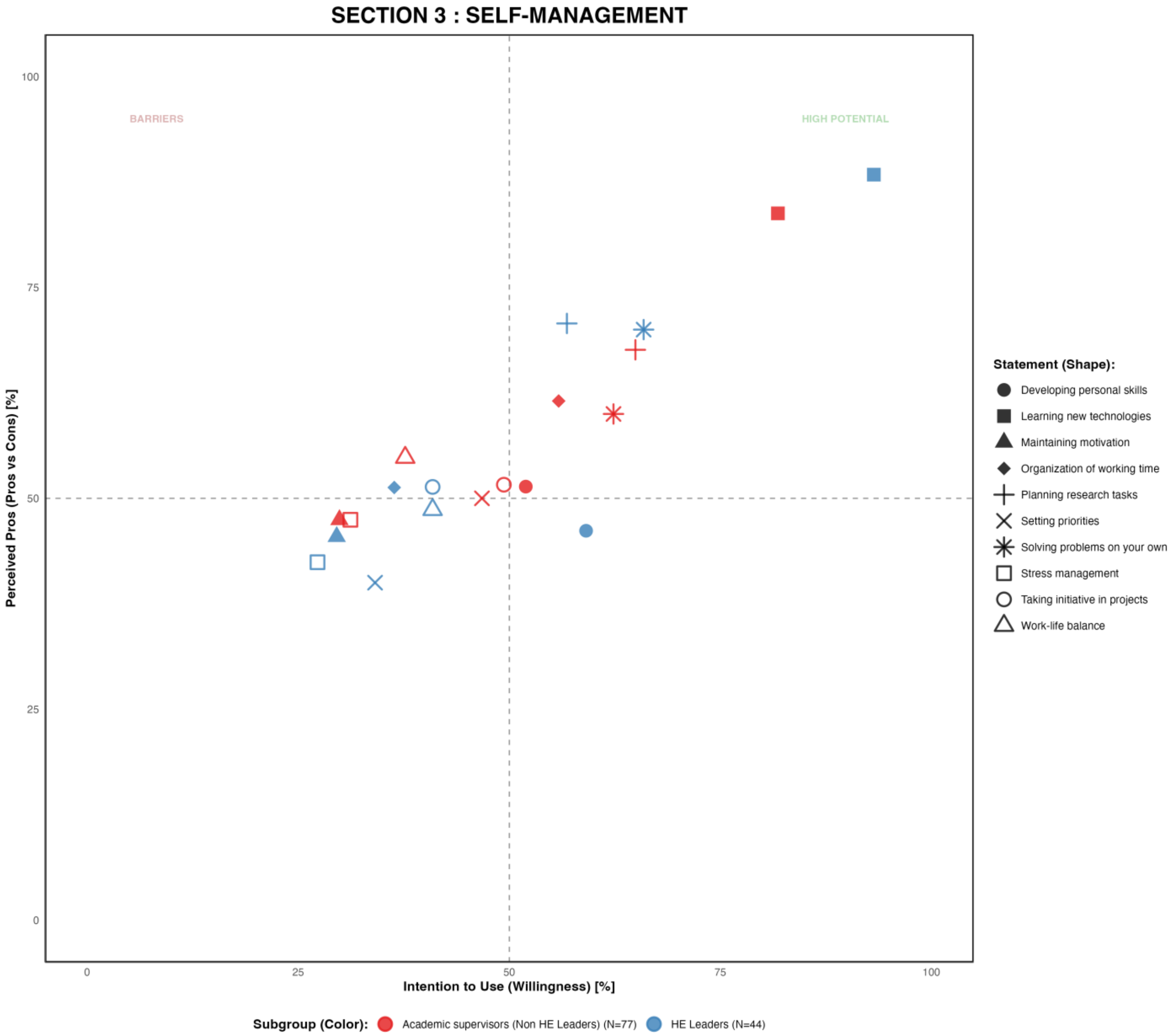


The results for the Working with Others domain reveal a striking and fundamental shift in respondent attitudes compared to the previous section. Across both groups, data points migrate almost entirely away from the High Potential quadrant, clustering instead in the lower-left area of the matrix, indicating that neither HE Leaders nor Supervisors regard AI tools as appropriate or beneficial within interpersonal and relational contexts.

The most pronounced resistance is observed among HE Leaders, whose scores for tasks such as conflict resolution, building professional relationships, and building mentor–mentee relationships fall as low as 15–25% on both axes. This reflects a deep-seated conviction, common in academic environments, that relational competencies are inherently human and cannot and should not be mediated by technological tools. Supervisors, whilst similarly sceptical, display a somewhat less extreme response, with scores generally clustering in the 30–50% range, possibly reflecting greater familiarity with structured HR tools in organisational settings.

A notable exception within both groups is giving and receiving feedback, which approaches or marginally crosses the 50% threshold - suggesting that where technology serves an administrative or process-structuring function, rather than substituting for genuine human interaction, a degree of acceptance remains. Interdisciplinary collaboration follows a similar pattern, with moderate scores indicating that tools facilitating knowledge exchange across departments are viewed with cautious openness. Overall, the findings draw a clear boundary between domains where AI assistance is welcomed and those where it is firmly resisted. Respondents appear to regard emotional intelligence, trust-building, and relational judgement as non-delegable human responsibilities. This has direct implications for the scope and framing of any AI-related training interventions developed within the project.

3.7.3 Self-management



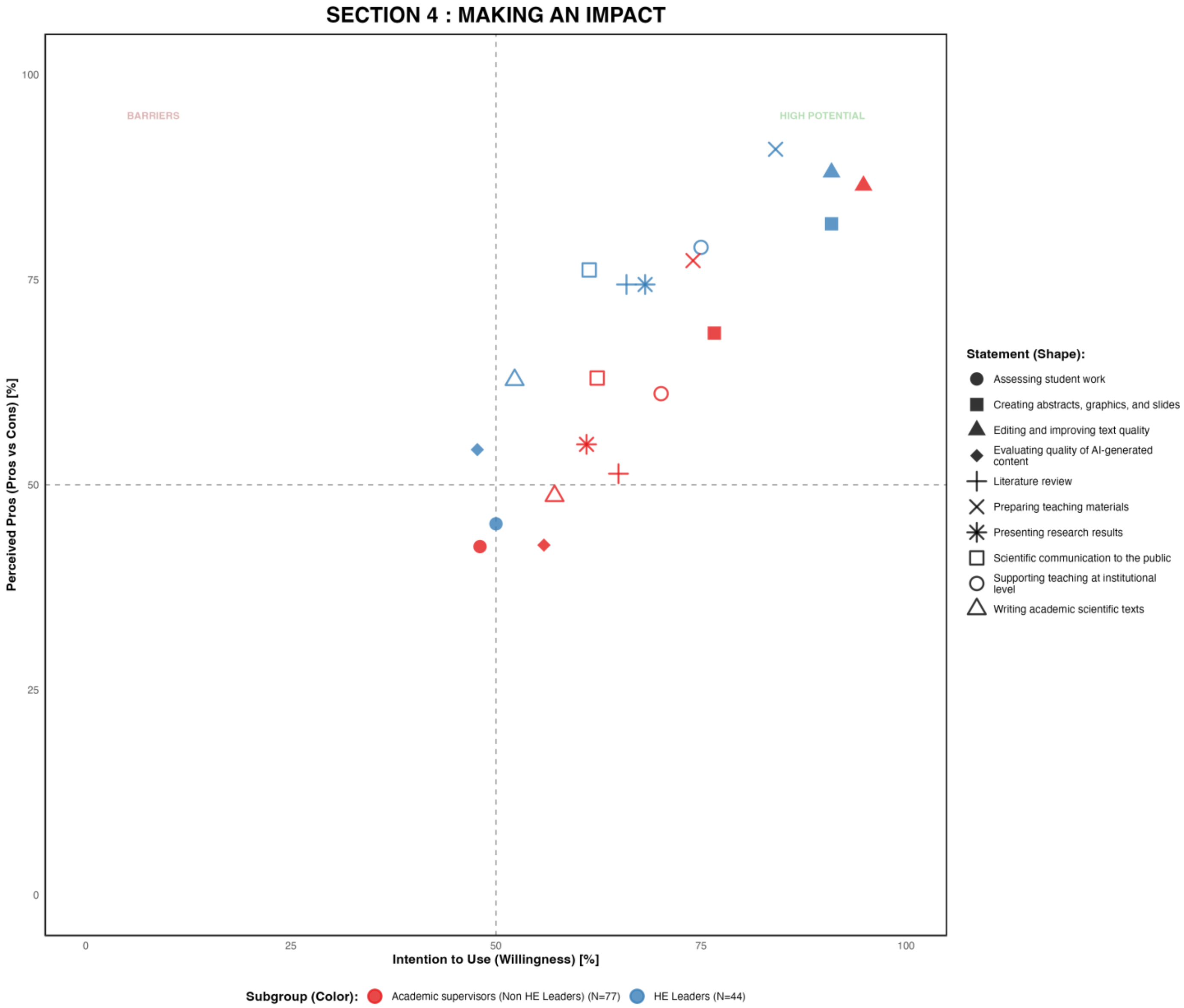
The Self-Management domain presents a more nuanced picture than either of the preceding sections, with data points distributed along a clear diagonal trajectory - reflecting a fundamental divide between task-oriented and emotionally-oriented aspects of personal management. At the high-potential end of the spectrum, learning new technologies stands out as the strongest result in the entire dataset, with HE Leaders placing it at approximately 90% on both axes. Planning research tasks and solving problems independently also score strongly across both groups, suggesting that respondents readily embrace AI tools when these serve a structuring or knowledge-retrieval function, an extension of the analytical receptiveness observed in Section 1. Developing personal skills sits notably close to the midpoint on both axes for both groups, indicating a cautious and conditional openness: respondents appear willing to consider AI support for skill development, yet stop short of expressing strong conviction, possibly reflecting uncertainty about how effectively technology can substitute for experiential or mentored learning in this domain.

Conversely, tasks associated with psychological self-regulation - notably stress management, maintaining motivation, and work–life balance - fall consistently below the 50% threshold on both dimensions, with HE Leaders displaying particularly pronounced reluctance. Setting priorities follows a similar pattern among academic respondents, likely reflecting the view that research agenda-setting is an intrinsically human, judgement-driven process.

A notable divergence between the two groups emerges around organisation of working time, where Non-HE Supervisors express moderate acceptance whilst HE Leaders remain considerably more reserved - consistent with the less predictable and more autonomy-driven nature of academic work.

Overall, the findings indicate that respondents approach self-management tools with considerable discernment, welcoming technological support for structured, cognitive tasks whilst firmly guarding personal autonomy in areas related to emotional regulation and well-being.

3.7.4 Making an Impact



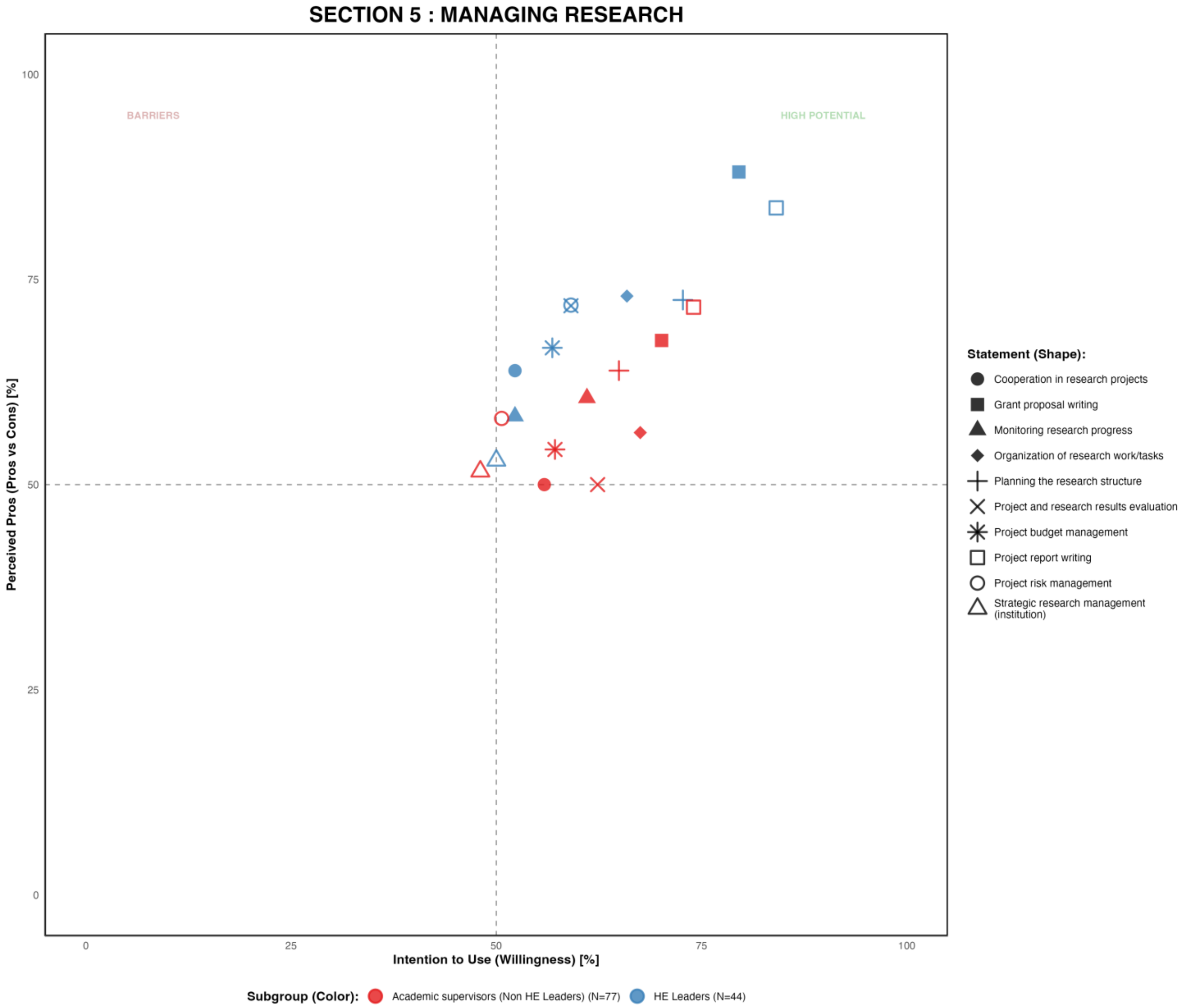
The Making an Impact domain sees a marked return to the High Potential quadrant, with both groups expressing strong enthusiasm for AI-assisted tools in content creation and knowledge dissemination. The clearest endorsements are reserved for tasks of an editorial and formatting nature: editing and improving text quality, creating abstracts, graphics, and slides, and preparing teaching materials all achieve scores exceeding 85% on both axes, with HE Leaders placing particular value on the latter - reflecting the considerable administrative burden that curriculum and instructional material development places on academic staff.

Tasks involving the aggregation and communication of existing knowledge - including literature review, presenting research results, and scientific communication to the public - occupy a middle tier, with scores generally in the 65–80% range. Respondents appear to regard AI assistance in these areas as genuinely useful whilst retaining a degree of caution, likely in recognition of the risk of inaccuracy and the continued need for expert verification.

The most pronounced reservations emerge around tasks carrying ethical or intellectual responsibility. Assessing student work records the lowest scores in this section for both groups, with willingness falling below the 50% threshold - indicating a strong consensus that evaluation of individual performance is a human prerogative that should not be delegated to automated systems. Similarly, writing academic scientific texts elicits limited willingness despite relatively higher perceived benefits among HE Leaders, suggesting an awareness of the potential value of AI support alongside significant concerns regarding authorship, academic integrity, and intellectual ownership.

Taken together, the results reflect a coherent and principled position: AI tools are embraced as operational assistants in the production and formatting of content, but firmly resisted where the task involves judgement, attribution, or accountability.

3.7.5 Managing research



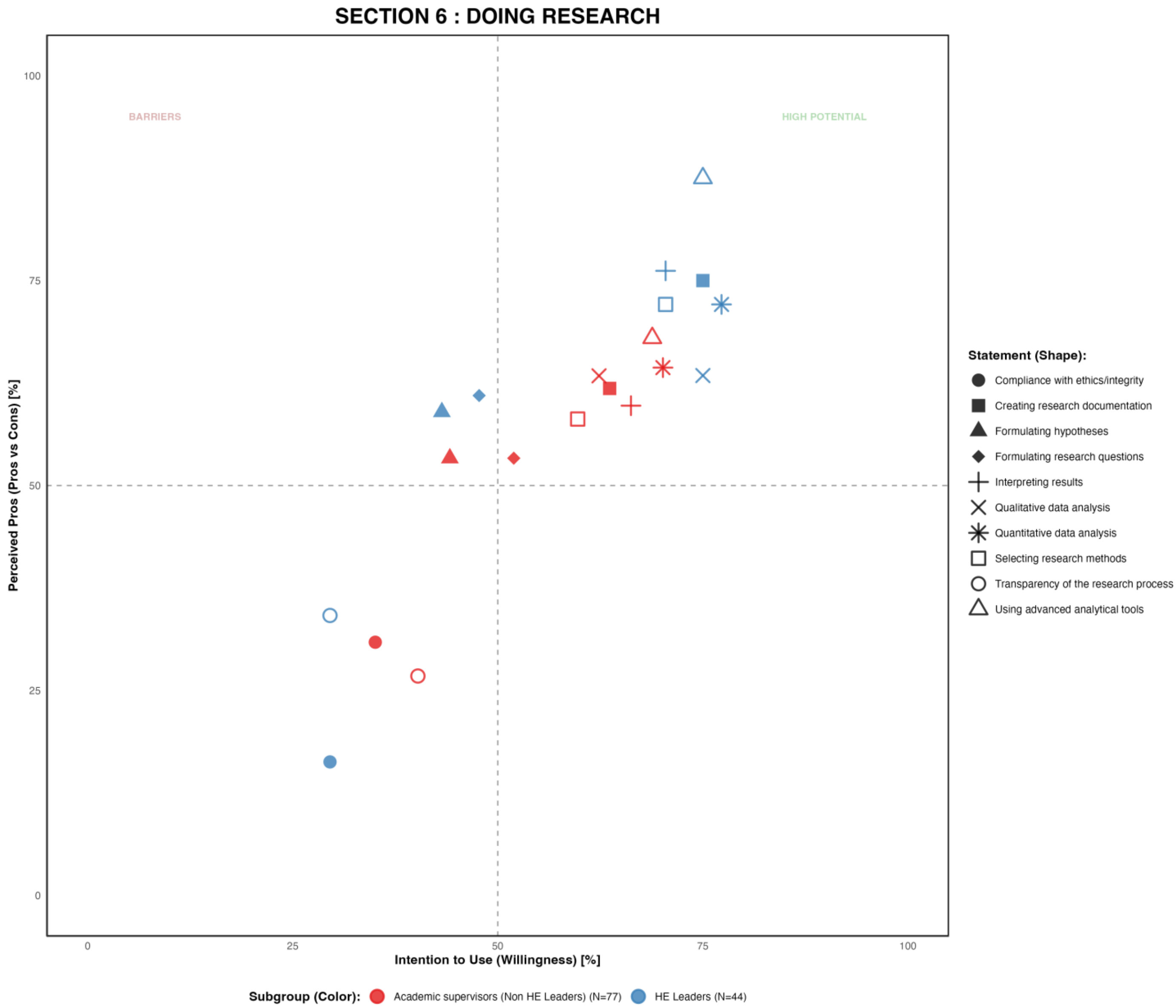
The Managing Research domain produces one of the most consistently positive distributions across the entire study, with virtually all data points situated within or close to the High Potential quadrant. The strongest endorsement by a considerable margin is reserved for grant proposal writing and project report writing, both of which achieve scores approaching or exceeding 85% on the perceived benefits axis among HE Leaders. This finding is readily interpretable: both tasks are characterised by rigid formal structures, prescribed vocabularies, and substantial time demands, yet contribute little to the intellectual substance of the research itself. Respondents evidently regard AI assistance here as a direct and measurable relief from administrative burden.

Operational and scheduling tasks - including planning the research structure, organisation of research work, monitoring research progress, and project budget management - form a coherent mid-tier cluster, with scores generally in the 60–75% range across both groups. The logic-driven, iterative nature of these processes lends itself well to technological support, and respondents appear comfortable delegating them to digital tools whilst retaining oversight.

A notable divergence between the two groups is visible throughout: HE Leaders consistently score higher than Supervisors (non-HE Leaders), likely reflecting the particular weight that grant cycles, compliance reporting, and project administration place on academic professionals, for whom such tools represent a more acute productivity gain.

The lowest scores in this section are recorded for strategic research management, cooperation in research projects, and project and research results evaluation - tasks that require institutional vision, relational judgement, or qualitative assessment. These results align closely with the patterns observed in Sections 2 and 3, reinforcing the broader finding that respondents draw a firm boundary at the point where process management transitions into leadership, strategy, or human collaboration.

3.7.6 Doing research



The Doing Research domain produces the most sharply polarised distribution observed across the entire study, with data points clustering distinctly at opposite ends of the matrix rather than forming a gradual diagonal. This binary pattern carries considerable interpretive weight.

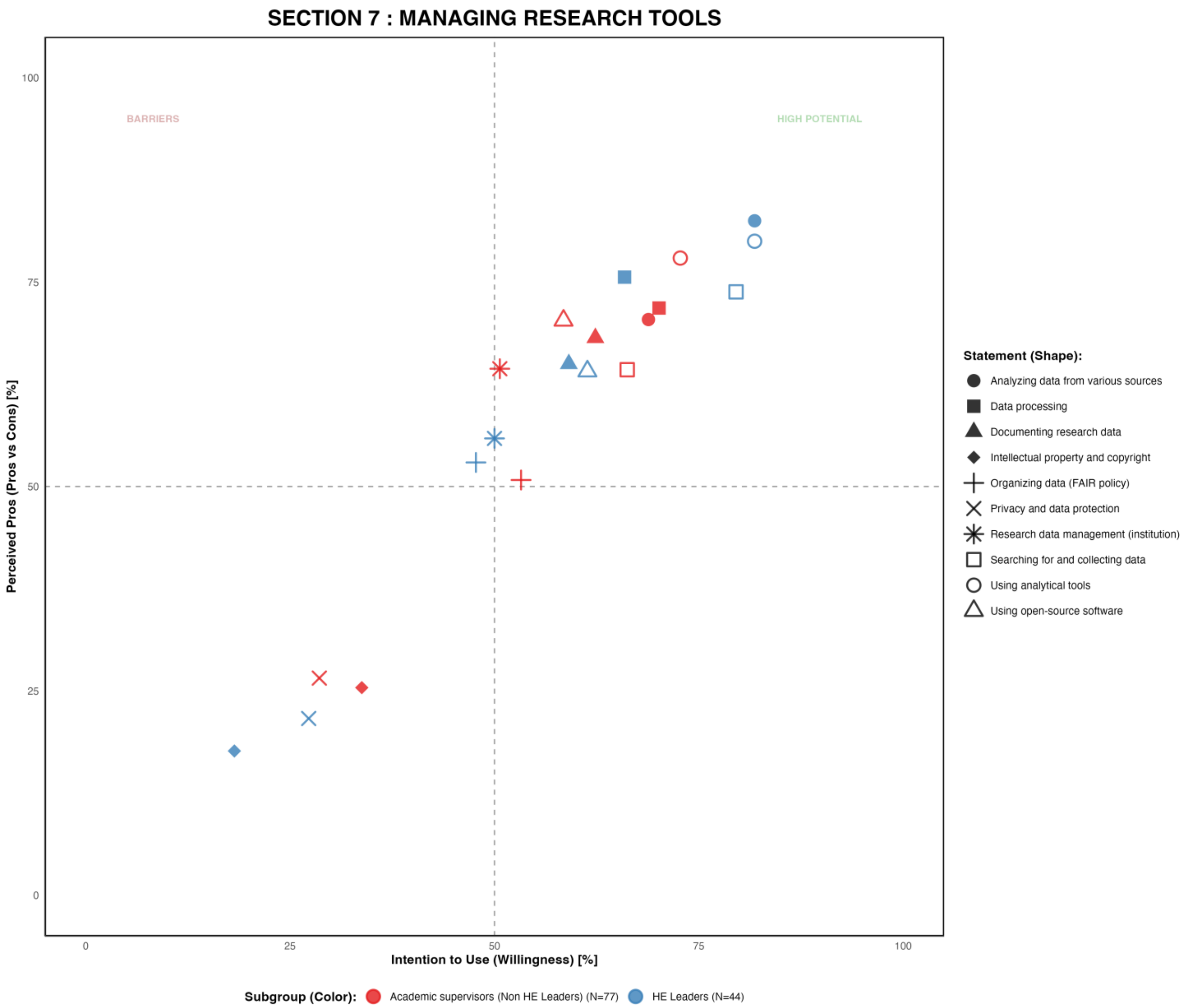
The High Potential cluster is anchored by using advanced analytical tools, which achieves the highest perceived benefits score among HE Leaders in this section - approaching 85% - alongside strong results for quantitative data analysis, qualitative data analysis, creating research documentation, and selecting research methods. Respondents across both groups clearly regard AI and digital tools as highly valuable in handling the computational and procedural dimensions of empirical research, where the capacity to process large volumes of data at scale constitutes an unambiguous efficiency gain. Interpreting results also scores positively, though with somewhat greater caution, suggesting that whilst tools may support the analytical process, final interpretive judgement remains firmly with the researcher.

A notably different picture emerges for formulating hypotheses and formulating research questions, both of which hover around the 50% threshold on both axes. Respondents appear to regard technology as a supplementary resource at best in these areas - useful perhaps for mapping existing literature, but insufficient as a substitute for the intellectual curiosity and disciplinary expertise that underpin genuinely original research enquiry.

The most striking finding in this section is the dramatic collapse in scores for compliance with ethics and integrity and transparency of the research process, which fall to the lowest values recorded across all six sections of the study - with HE Leaders placing the former at approximately 15% on the perceived benefits axis. This unambiguous rejection reflects a deep professional conviction that ethical responsibility in research is non-delegable: it cannot be transferred to an algorithm, and any suggestion to the contrary is regarded not merely as unhelpful, but as a fundamental threat to the integrity of the research enterprise itself.

In domains where the perceived risks of AI use outweigh the perceived benefits and declared willingness to engage remains low, a clear preference emerges for retaining human control - particularly in activities requiring evaluation, interpretation, and accountability for outcomes. This finding carries an important implication: AI systems should not be assigned self-regulatory functions, nor should they be permitted to autonomously assess their own outputs, as this risks the entrenchment of systemic bias arising from their internal operating mechanisms. Ensuring robust external human oversight therefore remains a fundamental condition for maintaining the credibility, transparency, and broader acceptance of AI applications within the research context.

3.7.7 Managing research tools



The Managing Research Tools domain presents one of the most sharply bifurcated distributions in the entire study, with data points concentrated at two distinct poles and a conspicuous absence of responses in the middle range. This binary pattern reflects a clear and principled distinction between tools that enhance productivity and those perceived as posing institutional or legal risk.

The High Potential cluster is led by analyzing data from various sources and using analytical tools, both of which achieve scores exceeding 80% on both axes among HE Leaders - the strongest results in this section. Data processing, searching for and collecting data, and using open-source software similarly attract strong endorsement across both groups. These tasks share a common characteristic: they are repetitive, time-intensive, and computationally demanding, yet carry no inherent legal exposure provided data are handled within secure and lawful parameters. Respondents readily delegate such work to digital tools, recognising the substantial efficiency gains on offer.

Tasks associated with institutional data governance - notably research data management and organising data according to FAIR policy - occupy a more neutral position, hovering around the 50–60% range. Whilst their value is broadly acknowledged, the procedural demands they impose appear to temper enthusiasm, particularly among those who regard compliance requirements as an administrative burden rather than an enabling framework.

The most striking feature of this section is the dramatic collapse in scores for privacy and data protection and intellectual property and copyright, which fall to the lowest values recorded - with HE Leaders placing the latter at approximately 15% on both axes. This near-total rejection reflects acute awareness of the legal and reputational risks associated with processing sensitive or proprietary material through external AI systems. In academic contexts especially, where originality and publication rights are foundational professional assets, the prospect of delegating intellectual property management to opaque algorithmic systems is regarded as institutionally unacceptable. The findings suggest that trust in AI tools is contingent not merely on functional utility, but on verifiable security and full transparency of data handling - conditions that, in respondents' judgement, are not yet reliably met.

3.8 Conclusions

Taken together, the seven strategic matrices present a coherent and internally consistent picture of how professionals across both higher education and non-HE sectors conceptualise the role of AI tools in their working lives. The findings do not reflect technological aversion; rather, they reveal a deliberate and highly rational framework for delegation.

A clear and recurring principle emerges across all sections: respondents willingly assign to technology those tasks that are repetitive, data-intensive, and procedurally bounded - including data analysis, report writing, content formatting, and project scheduling - whilst firmly reserving human authority over activities that require original thought, ethical judgement, emotional intelligence, or legal accountability. The boundary between these two domains is not arbitrary; it maps precisely onto the distinction between process execution and meaning-making.

A second cross-cutting finding concerns the emotional and relational domain. Across Sections 2 and 3 in particular, any task requiring empathy, trust, or interpersonal sensitivity was met with consistent and pronounced resistance. Respondents appear to regard human relationships as categorically non-automatable, and any technological intrusion into mentoring, conflict resolution, or personal well-being is perceived as a diminishment rather than a support.

Finally, the data reveal a pronounced ethical and legal threshold, most visible in Sections 6 and 7, beyond which technological enthusiasm collapses entirely. Where issues of data privacy, intellectual property, research integrity, or individual assessment are concerned, the opacity of AI systems is regarded as fundamentally incompatible with the standards of accountability and transparency that professional and academic contexts demand.

The consistent divergence between HE Leaders and academic supervisors further enriches this picture: first group display more extreme reactions in both directions, reflecting an environment in which administrative burden is acutely felt, yet scholarly authority and ethical rigour are defended with particular tenacity. Non-HE Supervisors, operating within more structured organisational frameworks, tend towards a more measured and pragmatic assessment throughout.