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Generative Artificial Intelligence (GenAI) in the research process – A survey of researchers' practices and perceptions

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ABSTRACT

This study explores the use of generative AI (GenAI) and research integrity assessments of use cases by researchers, including PhD students, at Danish universities. Conducted through a survey sent to all Danish researchers from January to February 2024, the study received 2534 responses and evaluated 32 GenAI use cases across five research phases: idea generation, research design, data collection, data analysis, and writing/reporting. Respondents reported on their own and colleagues' GenAI usage. They also assessed whether the practices in the use cases were considered good research practice. Through an explorative factor analysis, we identified three clusters of perception: "GenAI as a work horse", "GenAI as a language assistant only", and "GenAI as a research accelerator". The findings further show varied opinions on GenAI's research integrity implications. Language editing and data analysis were generally viewed positively, whereas experiment design and peer review tasks faced more criticism. Controversial areas included image creation/modification and synthetic data, with comments highlighting the need for critical and reflexive use of GenAI. Usage differed by main research area, with technical and quantitative sciences reporting slightly higher usage and more positive assessments. Junior researchers used GenAI more than senior colleagues, while no significant gender differences were observed. The study underscores the need for adaptable, discipline-specific guidelines for GenAI use in research, developed collaboratively with experts to align with diverse research practices and minimize ethical and practical misalignment.

1. Introduction

Research employing Generative Artificial Intelligence (GenAI) is rapidly expanding across fields and is anticipated to accelerate and transform scientific knowledge [1]. As in many other parts of society, the integration of GenAI into academic research is characterised by a wide range of attitudes, perceptions, and yet to be developed practices. Owing to the inherent uncertainties that come along with new technologies, fierce debates have emerged over the potential benefits, risks and challenges of using GenAI for research purposes (e.g. Ref. [2,3]). As the technology continues to reshape academic landscapes, understanding the adoption and impacts of GenAI in research practices becomes increasingly important. The currently evolving discourse surrounding GenAI within academia reflects a spectrum of engagement ranging from enthusiastic adoption [4,5] to cautious valuation [6,7] and scepticism [8–10]. Following an avalanche of opinion pieces and conceptual contributions, empirical studies offering valuable insights into GenAI's adoption, perceptions, and anticipated impacts across different scholarly activities are currently emerging. Studies acknowledge GenAI's potential for efficiency gains and enhanced research processes, on one hand, while also revealing researchers' concerns about transparency, misinformation, biases, and generally unknown implications on the other [11].

While existing research has provided a foundation for understanding the complexities of GenAI adoption, limited empirical work has systematically explored its diverse use and perceptions across academic contexts and research fields. This includes variations between disciplines or ways of conducting research, as well as potential disparities

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across career stages, gender and other demographics. Furthermore, question remain about not only *whether*, but *how* academics might use GenAI in research and how they assess its research integrity implications across various use cases. Indeed, research practices as diverse as planning experiments, writing project proposals, generating and collecting data, analysing it, reporting it or transforming it into lay-accessible content can all potentially be assisted or conducted by GenAI tools. However, whether researchers actually do this and how they assess research integrity aspects of using GenAI for these various cases, remains largely unknown.

While several actors are preparing policy interventions to steer the usage of GenAI in research (e.g., publishers, funders or research institutions aiming to govern particular research practices, e.g. Committee on Publication Ethics [12]), systematic understandings of researchers' own practices become increasingly important. Indeed, such policy initiatives tend to remain paper tigers if not properly aligned with practices of those they tend to govern [13]. This paper aims to deepen our understanding of GenAI's role in academia based on the results of a nationwide survey of researchers across Danish universities. By exploring how researchers from diverse backgrounds, fields and scholarly traditions use and assess the application of GenAI for a wide range of research tasks, this paper seeks to contribute to a more comprehensive understanding of GenAI's evolving role within academia. Ultimately, this is intended to inform the preparation of tailored guidelines and models of accountability.

1.1. *Overview of other relevant studies*

In examining the current landscape of GenAI within academia, several studies have offered insights into its adoption, perceptions, and anticipated impacts across various scholarly activities. While most studies have focused on the use of GenAI in educational and teaching contexts, several have also examined research contexts. Notably, a survey at a large U.S. research university revealed mixed attitudes among faculty and students towards GenAI, with a general openness to training despite low current usage and comfort levels, particularly in research contexts [14]. Contrastingly, a survey among higher education faculty reported a modest but growing integration of GenAI in research activities, marking a 13-percentage point increase between spring and fall 2023 (9 % vs. 22 %) [15].

A survey among users of ResearchGate and Academia.edu found that reasons for researchers to use GenAI in their work are mainly related to timesaving, self-efficacy, self-esteem and reduction of stress. Conversely, concerns over academic integrity and negative peer evaluations of GenAI usage, limit researchers' inclination to use GenAI tools for their work [16].

Additionally, several surveys were conducted in the context of the Nature portfolio of journals. A survey among authors of Nature articles and readers of Nature Briefing [11] found that while a large minority of researchers engaged with AI frequently, many expressed concerns about misinformation and biases, yet recognized benefits such as efficiency gains and improved accessibility for non-native English speakers. Another survey conducted by Nature among 3838 postdocs indicated similar level of engagement with GenAI, particularly chatbots, with 31 % of respondents reporting using chatbots. Interestingly, a majority (67 %) felt AI had not significantly altered their day-to-day work or career plans [17]. Similarly, a survey among readers of the Nature journal suggested a diversely engaging but cautious approach towards GenAI in academia [18]. Out of the 40 % that used GenAI at least occasionally, most report using it for coding tasks or to help write manuscripts, prepare presentations or conduct literature reviews.

Furthering this discourse, findings from a UK-based survey highlighted that over half of the academics utilized GenAI for efficiency, expecting its role to expand significantly [19]. This sentiment mirrors the European Research Council's [20] survey results, which anticipated AI (not necessarily generative AI) fostering faster academic processes and enhancing human-AI collaborations, albeit with concerns about potential ethical and transparency issues.

Apart from this host of survey studies on researchers' use and perceptions of GenAI, two other empirical studies are worth mentioning here. A systematic review of the literature on guidelines and standards on how to use GenAI and Large Language Models (LLMs) in academic medicine [21] came to five recommendations for which they feel there is sufficient consensus among the research community, including statements like Chatbots not being allowed as an author in scientific manuscripts; humans must be held accountable for use of ChatGPT/LLM and contents created by ChatGPT/LLM should be meticulously verified by humans. The study highlights the necessity for robust guidelines to govern GenAI's academic use, advocating for accountability in AI-generated content. This need for clarity and oversight is crucial as evidenced by Gray's [22] quantitative analysis, which discovered a noticeable uptick in LLM-assisted publications within engineering and natural sciences – a trend that highlights the differential adoption rates across disciplines. Gray estimates that up to 85,000 LLM-assisted articles were published in 2023, indicating significant adoption of GenAI in academic publishing, for which other papers have provided (more anecdotal) evidence too. We note that the literature of studies examining GenAI use in the research process is likewise quickly developing and any overview will inevitably only provide a snapshot of the current state of affairs.

Apart from empirical work on the adoption, perceptions and implications of GenAI in research contexts, the ethical implications of this new technology have been hotly debated. Multiple ethical principles in question have been highlighted and based on a literature review, Ning et al. [23] identified nine key principles to be used to build an ethical framework for GenAI use in health care: accountability, autonomy, equity, integrity, non-maleficence, privacy, security, transparency, and trust. These nine ethical dimensions are all related to broader ethical principles such as honesty (related to integrity) and fairness (related to equity). Ning et al. [23] use them to form a check list called "Transparent Reporting of Ethics for Generative AI (TREGAI)" that can be used to strengthen ethical considerations on the use of GenAI within health care and beyond. While these principles relate to the use of GenAI in multiple contexts, its use for research purposes raises additional questions, for example related to authorship issues [24], copyright and intellectual property [25], and reproducibility and open science [24]. While many have called for swift actions in terms of improved ethical guidance and regulations (e.g. Ref. [26]), others acknowledge the fast-moving nature of this technology and the implication that any regulation is doomed to become outdated or obsolete soon after its development. Based on a Delphi process involving a panel of scholars from the social sciences, law, ethics, and scientific publishing, researchers co-created a set of core principles informing the responsible use of GenAI in research. This approach aims to allow flexible use under conditions of diverse technological developments and stipulates researchers to adhere to (principles of) regulation, data security, quality control, originality, bias mitigation, accountability, transparency and wider impact [27]. The latter notably also included social and climate justice.

1.2. *Research objective and questions*

The empirical studies mentioned above collectively indicate an evolving uptake of GenAI technologies in the academic community. The insights reflect a spectrum of engagement, from enthusiastic adoption to fierce scepticism, which is still in flux. This evolution is evident in the significantly different results observed in subsequent waves of similar surveys. However, up to this point, studies have suggested some variations but have failed to systematically examine the diversity of GenAI use and perceptions across academic contexts. This includes variations between disciplines or ways of doing research, as well as potential variations across career stages and other demographics. In addition, relatively little is known about *how* academics use GenAI in their work and how they assess the research integrity of different GenAI practices, if they think of them as good or bad research practices.

In this study, we aim to address these knowledge gaps by conducting a nation-wide survey of researchers at Danish universities. We examine how researchers from various backgrounds and scholarly traditions use and assess the use of GenAI for a wide range of research tasks. In the remainder of this article, we will report the results of this survey and reflect on the implications for regulating GenAI use for research purposes. Our article will be guided by two research questions.

1. For what purposes and to what extent is GenAI applied for research at Danish universities by researchers across different disciplines/research fields, career stages and demographics?
2. What are the overall research integrity assessments of researchers towards the integration of GenAI in academic research? How do attitudes towards GenAI vary across different scientific fields, career stages, and demographics (e.g., gender, seniority)?

2. Methods

A description of the survey, the sampling process and analysis plan were described prior to launching the survey and uploaded to OSF [37].

2.1. Study participants

The survey was fielded as a census of all researchers at Danish universities. Previous studies have indicated that research practices and ways of producing knowledge, as well as researchers' assessment of good and bad research practices, strongly differ between researchers from different research backgrounds, demographics and institutional contexts [28]. Therefore, we aimed to reach researchers from all main areas of research. As the accessibility and legal framework impacting the use of novel technologies and generative AI in particular, differs across national contexts [29], we decided to field our survey in a single country, in order to minimize variation in this respect. Together, these considerations resulted in our choice of including all researchers including PhD students at Danish universities as our participants. Participants were sampled by collecting contact details from the institutional personal webpages of the researchers. A script was written to automatically collect the email addresses of all research staff of Danish universities. This resulted in 50,652 people with contact details and job titles. As we were only interested in staff members with research tasks, we selected all job titles that occurred at least 50 times (118 job titles) and suggested an academic position that might involve research tasks (leaving 88 different job titles). This resulted in 30,590 people. Removing duplicates (e.g. researchers working at multiple departments, hence having multiple email addresses) and inactive email addresses, the survey was sent out to 29,498 researchers including PhD students at Danish universities on Jan 22nd, 2024. Two reminders were sent to researchers who had not fully completed the survey and had not opted out of receiving further communication about it. These waves of invitations were sent to 27,978 and 26,670 researchers respectively. Before starting the survey, participants were asked to confirm that they are: "an active researcher at a Danish university holding a PhD degree (or equivalent)" or are "a PhD student".

Prior to sending out the full survey, 200 researchers were randomly selected from our sample to conduct a pilot survey. They received the full survey, with the additional request to flag any mistakes or phrases that were unclear. This led to minor adjustments of the survey instrument.

After concluding the survey, identifying information that had been used to contact respondents was removed, without links to other data sources. All analyses were done on this data set. The qualitative responses were further reviewed to remove potentially identifying information from the published data set.

2.2. Survey instrument and respondents

The full survey instrument can be found on the project's OSF page [37]. The survey consisted of two phases. In the first phase, we collected demographic and other background variables on the participants, including gender, academic age, native language, academic field and knowledge production ways (e.g. quantitative or qualitative social sciences, theoretical or experimental natural science, etc.), participants' exposure to institutional regulations and conversations about AI, and the extent to which they use GenAI either professionally or personally. In the second phase, participants were presented with 32 potential use cases of AI, divided into five research phases (see Table 1). For each use case, they were asked to consider if they had recently used AI for this purpose, if they were aware of colleagues with whom they had collaborated over the last year who had done so, and whether they considered the use case to be a good or problematic research practice. The survey concluded with two open questions asking respondents whether they had one or multiple specific GenAI tools in mind when completing the survey and providing them the opportunity to leave any additional comments they wanted to share.

Out of the 29,498 invitations, we received 2534 complete responses (8.6 %), with another 533 respondents answering part of the questions (1.8 %). Table 1 – table supplements 1–4 present an overview of the survey respondents and their self-reported demographic and disciplinary backgrounds. It also compares respondents' characteristics with

Table 1
Overview of use cases per research phase. ID column shows the codes used in the analyses, corresponding to the use cases.

Phase	Use case	ID
Idea Generation	help identify gaps in current research	idea1
	help identify relevant literature	idea2
	help summarize or analyse existing literature	idea3
	help identify potential collaborators	idea4
	help propose new hypotheses	idea5
Research Design	suggest a structure for research proposals	rd1
	help draft parts of a research proposal	rd2
	refine or edit language of research proposals	rd3
	refine or edit content of research proposals	rd4
	help design research methodology	rd5
	help develop theoretical models or conceptual frameworks	rd6
	help design experiments	rd7
Data Collection	suggest experimental parameters	dc1
	help formulate questions for surveys or interviews	dc2
	generate synthetic data sets	dc3
	transcribe recordings of research material (e.g. interviews, workshops or focus groups).	dc4
	identify ethical issues in research (either your own or someone else's)	dc5
Data Analysis	create or edit software code for data analysis	da1
	create or edit simulation software code	da2
	support statistical data analysis	da3
	help pattern recognition in data	da4
	create or modify scientific figures or images	da5
Writing and Reporting	suggest a structure for a research article	pub1
	help draft parts of a research article	pub2
	propose a title, abstract or keywords for your article	pub3
	edit a research article to improve readability and/or language	pub4
	format references	pub5
	identify strengths and weaknesses in a manuscript during the peer review process	pub6
	help write review reports during the peer review process	pub7
	translate one of your research papers into a different language	pub8
	help create (parts of) a slide deck for a conference talk or similar academic event	pub9
	help create lay summaries or similar non-academic writing for public engagement, based on your own texts	pub10

the full study population in terms of gender and disciplinary background. Gender of the non-respondents was inferred using first names and disciplinary background was inferred from non-respondents' departmental affiliation.

2.3. Description of quantitative analyses

All quantitative analyses were performed using R version 4.3.2. Multiple imputation was done using the 'mice' package [30].

The categorical academic age variable was constructed from a binary response on whether the respondent was a current PhD student, and a year for when the PhD-degree was awarded. We recoded these years to roughly correspond to the categories of European Research Council grant levels, so that respondents with a PhD from after 2016 are "starting", those with a PhD before 2017 and after 2010 are "consolidators" and those with a PhD from before 2011 are "advanced".

For the purpose of calculating aggregated scores and imputing missing values, we also created recoded versions of all numerical values of responses to personal use and the use of others, so that the responses "No" and "Not relevant for me" were recoded to 0, "Yes" to 1, and "Don't know" to missing value. Research integrity assessments were recoded for readability purposes only, as the value 1 corresponded to "excellent" and 7 to "very problematic". We reversed this scale and converted the value 8 ("Unable to answer") to missing values.

The multiple imputation was done in two batches, one for the two usage groups of variables, and one for the research integrity assessment variables. As the usage variables are binary, we used logistic regression, while we used predictive mean matching for the assessments. Both batches ran through 20 iterations.

The imputed data are used for both the reported aggregate scores and the factor analysis. Aggregated use scores are the mean use of an individual respondents, and corresponds to the proportion of use cases, the respondent has said "yes" to using GenAI for. The aggregated research integrity assessment is the mean value of these assessments, ranging from 1 (all use cases are rated very problematic) to 7 (all use cases are rated excellent).

Factor analysis was done using the 'psych' package in R [31]. We used parallel analysis to identify three factors with an eigenvalue above 1. We use a maximum likelihood factoring method with varimax rotation, to select factors with distinct peak loadings. The resulting loadings are high, with several peaks above .6, and 49.1 % of the variance explained. While the explained variance is not exceptional, we still consider it reasonable. Adding two additional factors would only explain 5.7 % more of the variance, which would not be justifiable, and introduce noisy factors.

Using the individual factor scores per observation, we cluster observations with *k*-means clustering with three centres, equivalent to the number of factors. Hierarchical clustering visually supports the number of clusters. These clusters group respondents while the factor loadings group the variables.

2.4. Description of qualitative analyses

The qualitative data we utilized was gathered from two open-text field questions included in the survey. The first question asked respondents about the types of GenAI tools they used, and the second, broader question sought their comments or insights related to using GenAI for research purposes.

The responses to the first question were compiled and visualized in bar graphs, segmented by gender, PhD age, research field, and whether the researchers were mono-disciplinary or multidisciplinary (Fig. 2 - figure supplements 1–5).

As for the second question, we received a total of 543 comments (excluding responses that indicated 'no comment'). To analyse the comments, we categorized the responses into emerging thematic groups: 'No comment', 'Understanding of the survey or elaboration of answers', 'Assessment of good or bad practice', 'Description of GenAI as a tool', 'Thoughts or issues related to policy, training, or infrastructure for GenAI', 'Examples of use', and 'General opinions or emotions about GenAI'. The comments and coding results can be found on the project's OSF site [37]. Here, we have removed any identifying information from the open text fields, including names, university details, department or specific research fields, and any particular activities mentioned by respondents that could lead to identification. To help us analyse the three clusters identified in this paper, we specifically focused on the 182 comments coded under 'Assessment of good or bad practice'.

3. Results

The purpose of this initial study has been to document the use of GenAI and research integrity assessments among researchers. It is therefore primarily descriptive, focused on gathering data and reporting and discussing evidence. The collection of literature informing the study provided an overview of the most present empirical research evidence in this fast-developing topic area. The potential key characteristics and factors for the use of GenAI and research integrity assessments among researchers were identified, operationalized, included, and measured in the study's data collection as reported in section two and this section. The study does not delve into potential causal factors behind differing perceptions of GenAI use, as this would require additional, nonstructured data, i.e. interviews which have not yet been collected.

3.1. Descriptive overview of main results

The survey was launched on January 22, 2024, and remained open until February 26, 2024, with one invitation and two reminders being sent to all researchers (incl. PhD students) of all eight Danish universities. Out of the 29,498 invitations, we received 2534 complete responses (8.6 %), with another 533 respondents answering part of the questions (1.8 %). In the analyses below, we only use the complete responses. The survey consisted of two main parts, one with questions regarding general GenAI experience and demographic background variables, the other presenting 32 use cases across five phases of research work (Table 1). For each use case, respondents were asked about their own use, the perceived use of others, and an assessment of the use case in terms of research integrity on a 7-point Likert scale from excellent research practice to very problematic research practice. Further details about the survey can be found in the methods section.

Respondents were generally well spread across disciplinary backgrounds and demographics. We refer to Supplementary Table 1-Supplementary Table 4 for a descriptive overview of respondents' background and demographics relative to the study population.

In this section, we present descriptive statistics on the use and research integrity assessment of the 32 cases of GenAI use in the research process. Fig. 1 presents a plot of the research integrity assessment and average use (both own use and the perceived use of colleagues) of each of the individual use cases. It shows a rather wide distribution of research integrity assessments for most use cases, indicating diverse opinions about whether using GenAI tools for these purposes constitutes problematic or good research practices. In general, respondents assessed using GenAI for language editing use cases (e.g. in proposal writing, editing of research articles, formatting references) and those related to data analysis (e.g. creating codes for analysis or simulation, pattern recognition, transcription of research recordings) as rather good research practices. In contrast, usage of GenAI for arguably more fundamental tasks related to designing research experiments or theoretical frameworks and critical assessment of other work during peer review was considered more problematic.

Two use cases that were particularly contentious were those related to the creation or modification of images and figures, and the creation of synthetic data. Both these cases might have different connotations in diverse research fields. An important observation in relation to the

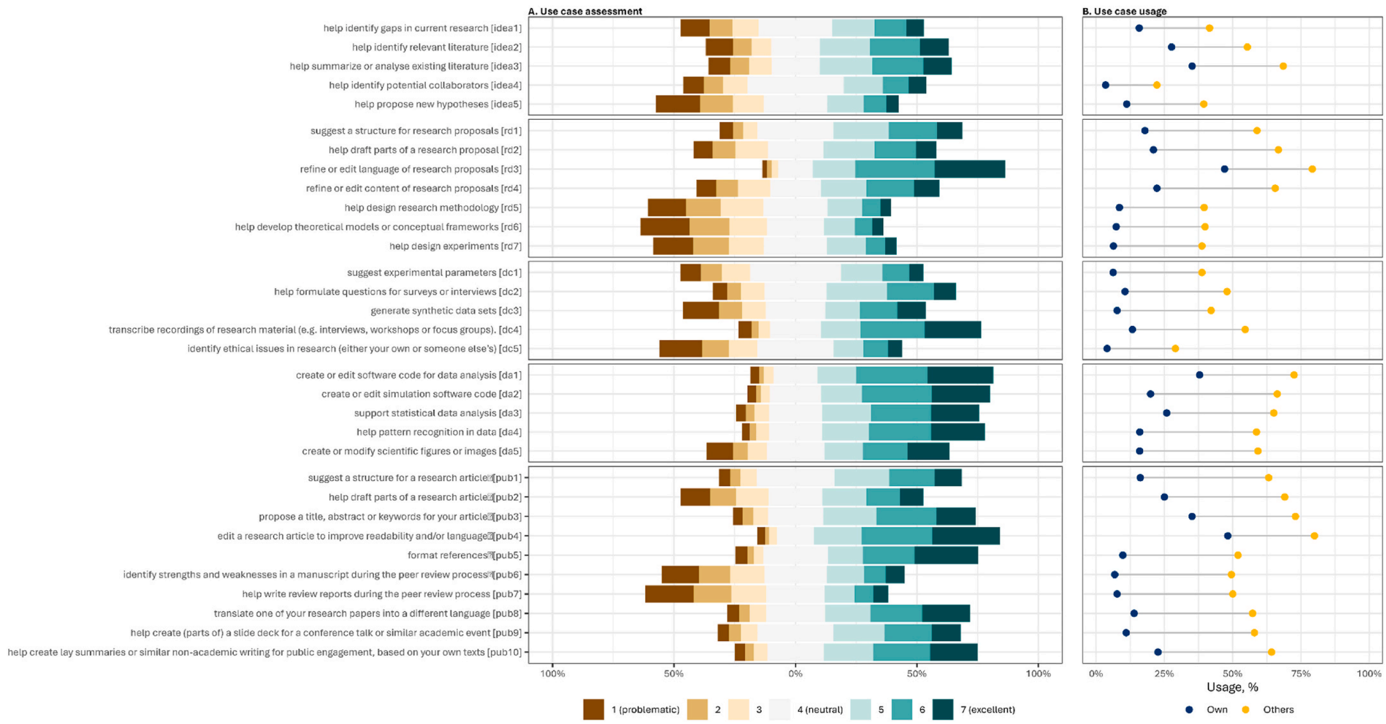

Fig. 1. Research integrity assessment scores and share of participants using GenAI for specific use cases. Results are shown by research phase. Brown bars show the shares of respondents judging the use case as a problematic practice, while green bars show positive assessments. Light gray bars are the share of neutral responses. Blue dots in the right panel show how large a share of respondents that report ever having used AI for the specific use case, while yellow dots show the share of respondents who report that they believe their colleagues use AI for this use case. Horizontal lines in the right panel serve as visual guides only.

research integrity assessment is that many respondents elaborate in the open text field of the survey [37], that their integrity assessment of the use of GenAI depends on it being used critically and reflexively. As one respondent puts it:

> *"Although I have answered in many cases that using AI is excellent practice, this does not mean that it should be used uncritically or without checking references etc. I just consider AI as giving an excellent head start on all of these tasks" (ID19826).*

The qualitative comments, allowing respondents to contextualise their responses, contain several descriptions indicating a lack of trust in GenAI. The main problems mentioned are hallucination (that the chatbot "makes up" information), violation of privacy rights and copyrights (not knowing what is allowed to be fed into e.g. GenAI tools), potential biases, and 'black boxing' of the generative process.

Generally, we observe a moderate positive correlation between the research integrity assessment of use cases and their admitted use by respondents (Kendall's $\tau = .44$) or their colleagues ($\tau = .5$). Some exceptions are the use of GenAI to identify potential collaborators and to create synthetic datasets (relatively low use), and to propose a title, keyword or abstract or even help draft parts of the body of an article (with relatively high admitted use). For all use cases, the reported use of GenAI of direct colleagues is higher than that of respondents themselves, with particularly large relative differences for the two use cases related to the peer review process (identifying strengths and weaknesses of manuscripts under review and writing review reports). This is in line with what is found in other surveys, e.g. focusing on questionable research practices and malpractice [32].

Last, we note that for almost all use cases, the share of respondents indicating a use case to be a good, very good or excellent practice is higher than the share of respondents indicating to have used GenAI for this purpose. This suggests that, while reported use of GenAI is still fairly low, the reason for not engaging in more use cases of GenAI is probably not primarily related to research integrity considerations.

This is further underlined by aggregated assessment and usage scores (see Supplementary Fig. 1), illustrating higher assessment scores, and lower variance, as usage grows. Respondents that had not used GenAI, or only had used it in very few use cases, had much higher disagreement on the assessment of the use cases on average.

Fig. 2 presents the aggregated use and research integrity assessment of all 32 use cases, broken down by research field (top panel), knowledge production ways (second panel), gender (third panel) and academic age (bottom panel). It shows relative consistency in responses across main research areas, with most users in all disciplines indicating to use GenAI tools for only few use cases. However, a somewhat larger proportion of respondents from the technical sciences, especially those in the experimental technical sciences, indicate to use GenAI for a higher number of different use cases, some even for more than half of all use cases mentioned in our survey. Simultaneously, respondents from the technical sciences have the highest aggregated research integrity assessment of our 32 use cases. In contrast, scholars from the humanities indicate to use GenAI tools least frequently and they also have the least positive research integrity assessment of the use of GenAI for research purposes. Some of the respondents from this main area of research indicate to have a strongly negative research integrity assessment of the usage of such tools for many use cases. A substantial share of respondents from the humanities (19.3 %) gives an overall assessment of 3 or less on a 7-point scale (i.e. degrees of 'problematic research practice').

Looking at differences within research fields, we note that quantitative social scientists indicate to use GenAI tools for substantially more use cases than their colleagues from the qualitative social sciences. Again, we notice the inverse pattern in terms of research integrity assessment, i.e. the qualitative social scientists giving slightly lower scores to the acceptability of using GenAI tools for various purposes.

In terms of gender, no differences in either use nor ethical assessment were observed between men and women. Some variations are reported in the other two categories (non-binary and 'do not wish to disclose'), but these contain only few observations.

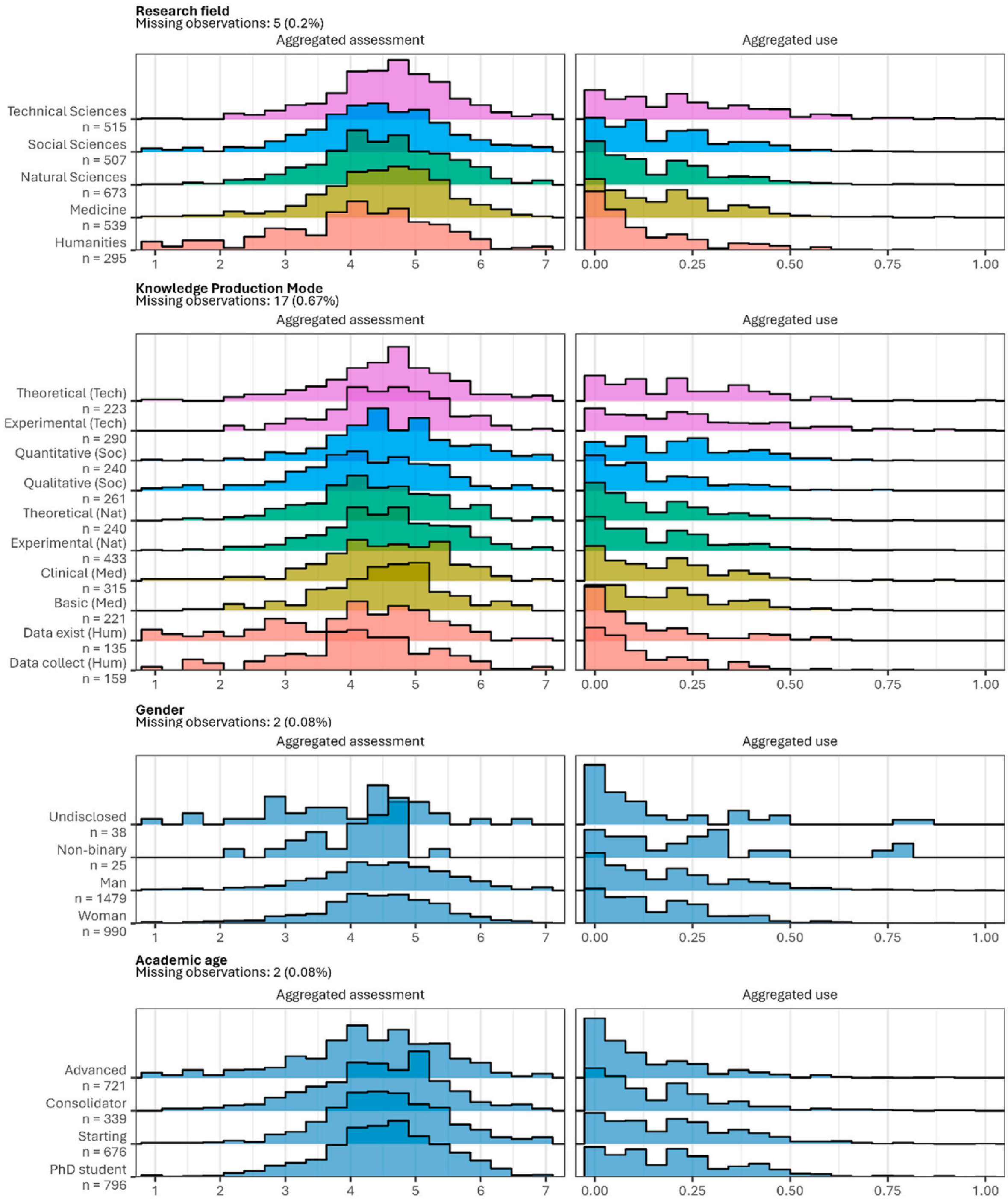

Fig. 2. Distribution of aggregated use and research integrity assessment scores. Each panel shows the aggregated research integrity assessment (left column) or aggregated use (right column) across research field, knowledge production ways, gender and academic age (top to bottom). Colours in knowledge production ways distributions correspond to colours in research field.

In terms of academic age, we observe a clear pattern in usage of GenAI tools, with more junior scholars using GenAI for more different purposes than their senior colleagues. In terms of research integrity assessment, no substantial differences between respondents from different academic ages were observed. This means junior scholars have been quicker to adopt GenAI tools for various use cases than their senior colleagues, even with similar assessment of the appropriateness of such usage.

If we look at the GenAI tools that respondents had in mind when answering the survey, most respondents indicated to be thinking of ChatGPT (n = 1550), while 894 respondents answered 'no' or did not answer the question about if they had any specific tools in mind while answering the survey (Fig. 2 – figuresupplement 1). Copilot (both Microsoft and GitHub) was the second most mentioned tool (n = 176). Other tools mentioned include Grammarly (n = 101), Google's Bard (n = 76), Dall-E (n = 74) and DeepL (n = 69).

3.2. *Factor analysis*

We used exploratory factor analysis to identify patterns in the variance of research integrity assessments. We identified three clusters, supported by the eigenvalues in the parallel analysis (Supplementary

Fig. 7). We also checked the correspondence between observed and multiply imputed responses (Supplementary Fig. 8) and consider the correspondence sufficient to incorporate imputed responses for a more complete data material. Factor loadings underlying the cluster analysis are available in Supplementary Fig. 9.

The factor analysis revealed three clusters of research integrity assessment of GenAI use cases among respondents (Fig. 3), based on a *k*-means clustering of individual factor scores. The clusters differentiate from each other by highlighting different types of integrity assessments of GenAI use in research. **Cluster 1** could be labelled **"GenAI as a work horse"**, with 893 respondents (35.2 %). In this cluster we find researchers who consider using GenAI to create and edit software codes for analysis and simulation (da1-2), to support statistical analysis (da3) and to help recognize patterns in data (da4) as good research practices. On the other hand, researchers in this cluster are more sceptical towards using GenAI in the peer review process (cf. pub6 and pub7) than researchers in the two other clusters. They also score using GenAI in the 'Idea generation phase' (idea1-5) lower than researchers in the other two clusters. If we look at the comments from researchers in this cluster, made in the open text field in the survey [37], some researchers, point out that GenAI *"is good when used for tedious tasks like formatting, editing, generating a code for idea that you have in mind, generating drafts, etc, and terrible for creative tasks" (ID2561),* that it is *"problematic to be using generative AI in creating articles or other written materials" (ID13760)*, but that GenAI can be good for *"checking language and reviewing code" (ID12608)*. This cluster is thereby mainly characterised by using GenAI as a tool to speed up, process, or help researchers with technical issues in relation to their research – i.e. as a "work horse".

In **cluster 2** – tentatively called **"GenAI as a language assistant only",** we find the most sceptical respondents (n = 609, 24.0 %). They generally assess the use of GenAI more negatively than the other clusters, but it is also in this cluster where we find the most "neutral" responses. Positive assessments are mainly found for use cases related to language editing, e.g. refine and edit language of research proposals (rd3), transcribe recordings of research material (dc4) and propose titles, keywords, or abstracts, edit research articles for readability and formatting references (pub3-5). Particularly, cluster 2 researchers find it more problematic to use GenAI for data analysis (da1-5) than researchers in the other two clusters. In the open text field comments from cluster 2, researchers provide some clarification of this pattern. Respondents referred to GenAI as *"a glorified spell checker" (23440),* and mentioned that it is potentially useful *"[n]ot so much in actual research, but for various kinds of help-services, especially in connections with language polishing/translation and editing" (20622)*. Overall, it seems that researchers in this cluster are generally sceptical towards using GenAI for research purposes, potentially with the sole exceptions of using GenAI as an assistant in the more "language related" aspects of the research process. The positive assessments are very few and weak in this cluster.

Finally, in **cluster 3,** which could be labelled **"GenAI as a research accelerator",** we find 1032 researchers (40.7 %) who are generally very positive in their assessment of GenAI. They are positive about using GenAI in almost all use cases, particularly in relation to data analysis and research design. There are only a few use cases with a slightly more varied/negative assessment, e.g. the creation of synthetic datasets (dc3) and identifying ethical issues in research (dc5). Again, the comments do not directly explain why the researchers in this cluster score these use cases as they do. The comments deal with many different issues, but some researchers mention that using GenAI tools help them become more productive:

> *"I do believe that AI is excellent practice for increasing productivity especially in the form of content/outline SUGGESTION (not copy-pasting it for the final version of a paper as content might be faulty and is often too general), language improvement (here AI is excellent and I don't see any ethical/moral problems with it as long as input data is not confidential), and generating first drafts of sections based on my own (unstructured) content/thoughts (again, I do not see any problem with that as the content still comes from me)." (ID20164)*.

In terms of reported use, all three clusters follow a similar pattern regarding the use cases for which higher/lower use of GenAI is self-reported. The clusters only differentiate in the extent to which they report higher/lower use, with respondents in cluster 3 consistently reporting highest use for every use case. Hence, while we observe relatively strong differences in terms of research integrity assessment,

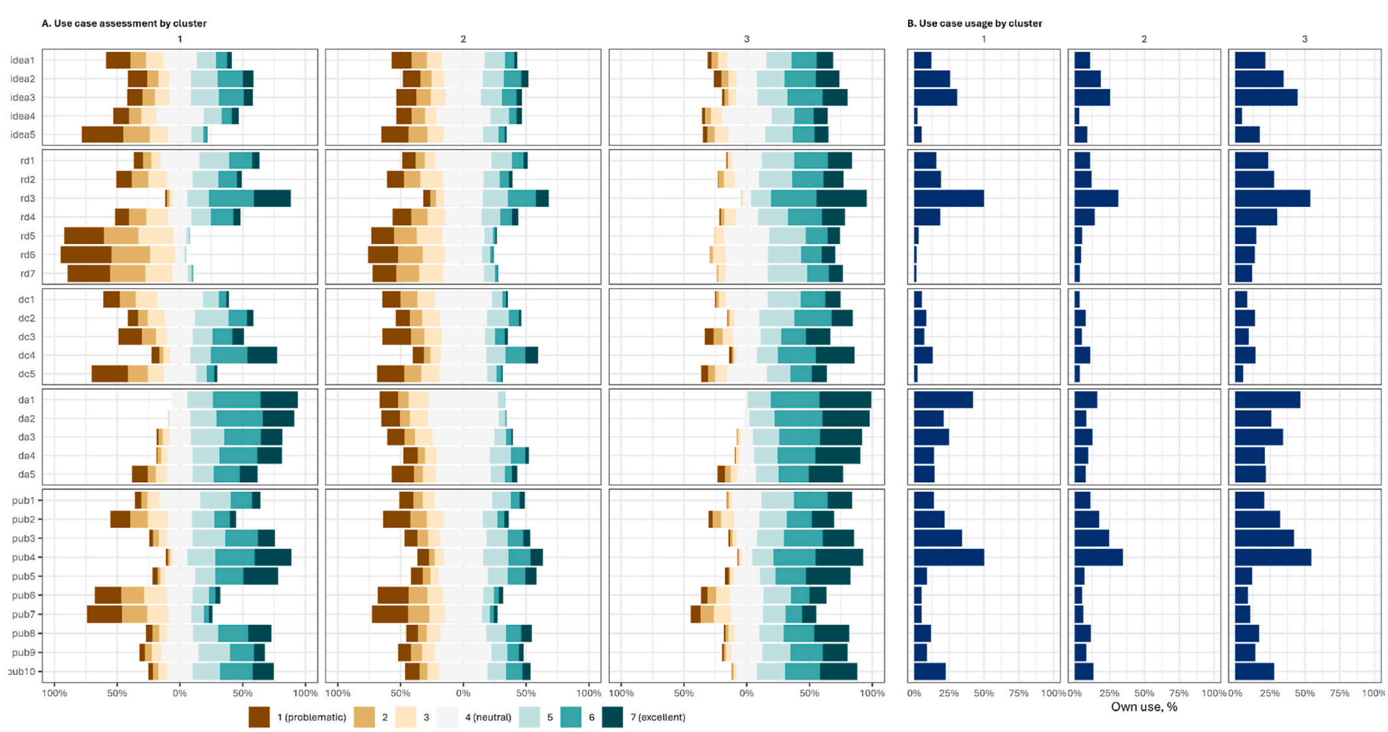

Fig. 3. Research integrity assessment responses and own use across all use cases, split by factor loading clusters.

these only weakly reflect in respondents' self-reported use of GenAI across different clusters.

If we look at the demographic distribution of respondents over the three identified clusters (Fig. 4), we do not find any differences in how men and women assess the research integrity of different GenAI use cases. Similarly, there are only minor differences in how different seniority groups (PhD students, and starting, consolidated and advanced researchers) assess what is good use of GenAI. Only in relation to main areas of research and knowledge production ways, we find more pronounced differences.

In cluster 1 – "GenAI as a work horse" – we find researchers from all types of epistemic backgrounds. However, researchers from the humanities, who work on data produced by themselves (26.4 %), clinical medical researchers (30.5 %), and theoretical natural scientists (31.7 %) are less well represented in this cluster compared to researchers working with other ways of producing knowledge, who have a representation of between 34.1 % and 40 % in cluster 1.

In cluster 2 – "GenAI as a language assistant only" – we find a bigger proportion of humanities scholars (36.6 %) compared to the other four main areas of research (from 20.6 to 23.4 %). If we look at differences between researchers using different knowledge production ways, we similarly see that a greater proportion of the humanities scholars, who work on data produced by themselves, are to be found in cluster 2 (41.5 %), compared to the other nine knowledge production ways. However, many theoretical natural scientists (32.1 %), humanities scholars working on existing data (30.4 %), and qualitative social scientists (29.9 %) can also be found in this cluster of GenAI sceptics. Whereas, in comparison, much fewer quantitative social scientists (13.8 %), experimental natural scientists (17.8 %), basic medical scientists (19 %) and experimental technical scientists (19.3 %) are represented in this cluster.

In cluster 3 – "GenAI as a research accelerator" – we find a smaller proportion of researchers from the humanities (32.9 %) compared to the other main areas of research. For example, in the technical sciences, 44.1 % of researchers belong to this cluster, and in medicine it is 42.9 %. If we look at the 10 different knowledge production ways, the humanities scholars are joined by the qualitative social scientists (33.3 %) and

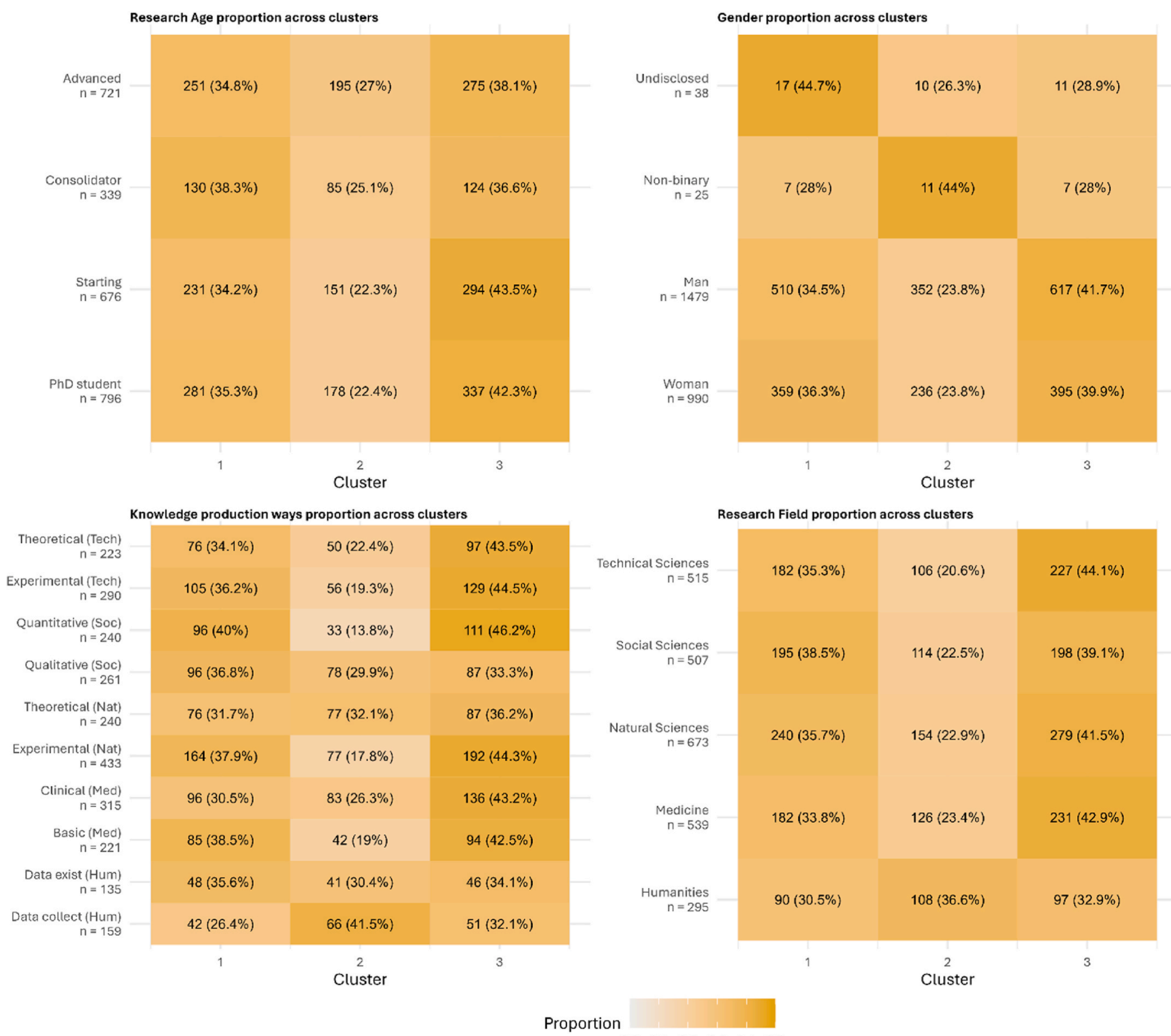

Fig. 4. Demographic distribution of respondents over factor clusters. Each heatmap shows the distribution of research age, gender, knowledge production way and research field for the three clusters of observations identified in the factor analysis.

the theoretical natural scientists (36.2 %) in being proportionally less represented in this cluster compared to other knowledge production ways.

4. Discussion

In this study, we set out to explore the use and assessment of GenAI in various research practices across gender, seniority, main areas of research, and knowledge production ways. The results show that there were no or only very minor differences in the use and assessment in relation to gender. Some variations were found related to seniority and bigger differences were found related to the different main areas of research. As Fig. 2 shows, both the patterns of use and assessment are fairly similar within and across main areas of research.

An interesting finding of the study, which nuances these minor differences, is that we find the largest disagreement of how to assess the research integrity of particular use cases – how good a practice they are perceived to be – in the group of the non- or infrequent users. This means that the agreement in assessment increases with use and indicates that familiarity with GenAI leads to similar, usually more positive, evaluations. This points to a need for more training for researchers within all fields; a need which is also echoed in a number of the qualitative comments to the survey.

This difference in use – that some use GenAI more than others – is further highlighted in the factor analysis presented above, where three main clusters of GenAI users in Danish academia are identified: “GenAI as a work horse”, “GenAI as language assistant only”, and “GenAI as a research accelerator”. Interestingly, the *use* patterns across the clusters are remarkably similar, but the degree of use differs. This means that the researchers in the three clusters use (and do not use) GenAI for the same things, but to a varied degree. We also observe a moderately positive correlation between research integrity assessment of use cases and reported use of the same cases. Our data do not allow identification of the direction of causality (i.e. whether more use creates a more positive view of GenAI or the other way around). Nevertheless, this correlation is fairly weak, and many respondents report positive assessments of use cases but no actual use of them. This suggests that non-use is often reported not because of research integrity concerns but due to other reasons, such as lack of awareness that GenAI can be used for this purpose, insufficient skills on how to use GenAI or a lack of confidence that peers will approve of GenAI usage and concerns about potential negative consequences.

However, the factor analysis also reveals some interesting differences between disciplines and different ways of producing knowledge *across* the three clusters. These differences are most pronounced in “GenAI as a research accelerator” (Cluster 3) and in Cluster 2, “GenAI as a language assistant only”. In Cluster 3, the most GenAI-positive group, we find mostly researchers from the technical and medical sciences, as well as quantitative social scientists and experimental natural scientists. In Cluster 2, on the other hand, we have more researchers from the humanities, qualitative social science, and theoretical natural science compared to other knowledge production ways. This pattern might reflect important differences in the way in which knowledge is produced; in the methods used and the overall approach to doing research, including the normative frameworks associated with these diverse approaches to knowledge production.

This difference can be described as a difference between nomothetic and ideographic research areas ([33] [1894]) – or perhaps more precisely, between more positivist ways of doing research, on the one side, and interpretative approaches on the other side. It seems clear that the more interpretivist researchers are more sceptical towards GenAI, and that they also use the “neutral” option more than the other clusters. This may be because use cases are seen as irrelevant to their research approach, e.g. generating hypotheses or suggesting experimental parameters.

Our study also demonstrates the complex interplay between regulations and community norms in shaping responsible GenAI use. While top-down regulations can provide a clear framework for good research practices, their effectiveness is contingent on their alignment with the values and practices of the research community. The case of peer review exemplifies this dynamic. It is among the few use cases surveyed in our study for which clear guidelines exist, prohibiting the use of GenAI for this purpose [34]. Simultaneously, we observe that this use case is among those with the strongest moral objections, perhaps influenced by the guidelines themselves. However, it is equally plausible that the guidelines were formulated in response to perceived pre-existing community concerns. This interplay highlights the need for a balanced approach to regulating GenAI in research. While top-down frameworks may help shape standards, rigid, top-down frameworks that disregard community norms risk being ineffective or even counterproductive [35]. Conversely, a purely bottom-up approach may lead to inconsistent practices and tensions between diverse research areas. In addition, our respondents indicate a clear desire for more support from their institutions (e.g. training and access to relevant infrastructure), to allow for well-considered and responsible use of GenAI for research purposes.

The latter touches on the wider ethical considerations of using GenAI for research purposes. As outlined by others, GenAI poses various ethical challenges to researchers [27]. Our survey adopted relatively inclusive terms to refer to such ethical considerations when asking for respondents’ assessments. We used the language of ‘responsible research practices’ in relation to specific research tasks, thereby likely triggering assessments of ethical aspects most closely related to integrity and privacy [23]. In their responses to the open questions, some of our respondents nevertheless referred to wider ethical principles including those of equity, fairness and accountability. The broader impact of using GenAI, including issues such as social and climate justice and referred to as the final principle in Knoechel et al. [27] framework for responsible GenAI usage, were hardly explicitly touched upon by our respondents though. In contrast, issues such as accuracy, trustworthiness and privacy were omnipresent in our respondents’ comments. This aligns well with calls for regulation noted by ethicists Resnik and Hosseini [36].

4.1. Limitations

While our study provides valuable insights into the use and assessment of research integrity of GenAI in the research process across various research fields in the Danish university context, it is important to acknowledge a number of limitations that may influence the interpretation of the findings and their generalizability.

First, there might be different interpretations among survey participants of what constitutes a GenAI tool. While many researchers thought about tools like ChatGPT when filling in the survey, others had more general tools in mind like Grammarly. Other researchers note that they had highly specialized tools in mind, developed for particular research tasks. This variation can influence the reported use and research integrity assessments of the tools. Similar considerations might have affected the interpretation of use cases, which might have different connotations within different knowledge production ways and epistemic cultures (e.g. the creation of ‘synthetic data’).

Second, the study is based on responses from a specific subset of Danish university researchers. The sample may not be fully representative of the entire Danish academic community, considering potential biases in who chose to participate in the survey. The low number of respondents in certain categories, e.g., non-binary and “do not wish to disclose gender” options, also constraints the ability to draw any conclusions for these specific groups. Moreover, respondents might underreport or overreport the use of GenAI tools and their research integrity assessments due to personal beliefs or perceived expectations. Research integrity assessments are subjective and vary based on individual values, backgrounds, and disciplinary/field norms [22]. This diversity may lead to a wide range of integrity assessments for similar use cases. The distribution of research integrity assessments indicates that there are many different opinions on GenAI use, which might be influenced by individual skills and experiences, field and disciplinary standards, and personal ethics. Social desirability might, for example, have played a role in how researchers have answered.

Third, the field of GenAI is evolving fast, and tools and their applications can change drastically over short periods. New tools emerge and existing ones are updated, potentially changing use patterns and research integrity perceptions. Therefore, our findings should be considered a snapshot of the state of affairs at a specific time and context, not necessarily generalizable to other settings.

Fourth, our study does not extensively explore the influence of cultural and institutional factors on the use of GenAI tools and research integrity assessment of use cases. Universities may have different policies and support structures that impact on how researchers engage with the tools.

Finally, while we studied a broad array of GenAI use cases, there are obviously other potential applications of GenAI in research that were not covered in our research. Future studies could expand the range of GenAI tools and use cases to provide a more comprehensive picture.

5. Conclusion and implications

Based on an initial collection of empirical evidence on the use of GenAI and research integrity assessments among researchers, this study has addressed pressing issues regarding GenAI's application, perceptions, and ethical dilemmas in research. This provides a necessary base for, and points towards important future research still to come. Among these are e.g. augmented empirical data to identify causal factors behind diverse perceptions of GenAI use and patterns of adoption, barriers and scepticism across researchers of diverse backgrounds. Such follow up is required to provide more in-depth evidence-based interpretability and recommendations for policy and support frameworks in academia.

Owing to the fast development of GenAI and its many different applications for research purposes, it is currently challenging to propose clear recommendations or guidelines for its usage. Any regulations proposed are likely to become obsolete quickly due to the speed of technological advancements. Therefore, we suggest following Knoechel et al. [27] approach in drafting principles that are flexible enough for implementation across various research fields. This approach is also supported by our data, which indicates that regulations and guidelines have to take disciplinary differences (i.e. differences in knowledge production ways) into account to be effective. To ensure successful integration, we suggest developing tailored strategies for diverse research contexts, working closely together with experts in those specific fields. Such a collaborative approach would ensure that strategies are tailored to the specific needs of the single research environments, thereby minimizing the risks of misalignment with the practices and experiences of individual researchers. Local workshops, focus groups, and other collaborative activities could facilitate such a process, and it is recommended to involve the research community at large, including researchers as well as learned societies, funders, publishers, and university administrations.

CRediT authorship contribution statement

Jens Peter Andersen: Writing – review & editing, Writing – original draft, Visualization, Validation, Software, Project administration, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Lise Degn:** Writing – review & editing, Writing – original draft, Validation, Project administration, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Rachel Fishberg:** Writing – review & editing, Writing – original draft, Visualization, Validation, Project administration, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Ebbe K. Graversen:** Writing – review & editing, Writing – original draft, Validation, Project administration, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Serge P.J.M. Horbach:** Writing – review & editing, Writing – original draft, Validation, Project administration, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Evanthia Kalpazidou Schmidt:** Writing – review & editing, Writing – original draft, Validation, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Jesper W. Schneider:** Writing – review & editing, Writing – original draft, Visualization, Validation, Project administration, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Mads P. Sørensen:** Writing – review & editing, Writing – original draft, Visualization, Validation, Project administration, Methodology, Investigation, Formal analysis, Data curation, Conceptualization.

Ethics declaration

The study obtained ethical approval from the Ethical Review Board of Aarhus BSS, Aarhus University, under document number: BSS-2023-132.

Declaration of competing interest

The authors declare no competing interests.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.techsoc.2025.102813.

Data availability

Anonymised data is available at https://doi.org/10.17605/OSF.IO/6HTFS.

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