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University staff and student perspectives on competent and ethical use of AI: uncovering similarities and divergences

Manoj Ravi[1*], Kashmir Kaur[2], Clare Wright[2], Matt Bawn[3,5] and Luisa Cutillo[4]

*Correspondence:
Manoj Ravi
m.ravi@leeds.ac.uk
[1]School of Chemical and Process Engineering, University of Leeds, Leeds LS2 9JT, UK
[2]School of Languages, Cultures and Societies, University of Leeds, Leeds LS2 9JT, UK
[3]School of Molecular and Cellular Biology, University of Leeds, Leeds LS2 9JT, UK
[4]School of Mathematics, University of Leeds, Leeds LS2 9JT, UK
[5]School of Natural and Environmental Sciences, Newcastle University, Newcastle upon Tyne NE1 7RU, UK

Abstract

We investigated the similarities and differences in understanding among UK-based university staff and students regarding AI literacy, in terms of competent and ethical use of AI tools. This study builds on existing research revealing both wide use of AI tools in higher education, but also a lack of shared understanding among stakeholder groups on what constitutes competent and ethical use of AI. This study is one of the first to combine insights from staff and students, illustrating specific concerns over AI competence and ethical implications in granular detail. The results reveal a significant disparity in the use of AI tools between students and staff, particularly in the adoption of text-based or conversational GenAI tools (cGenAI). Students reported extensive use of cGenAI tools for a range of tasks, while staff engagement was generally limited to brainstorming ideas or generating teaching tasks. Although the use of cGenAI is seen by most as AI competence, nuanced differences emerged between staff and student opinion depending on the application of the AI tool. Ethical issues in both groups were prominent, although staff reported more negative systemic concerns regarding inherent bias, concerns over transparency and data ownership. Over 90% of staff flagged the use of cGenAI for essay-generation as problematic, compared to 58% of students, primarily due to concerns regarding academic integrity. These differences point to the need for institutional guidelines and dialogue to address ethical concerns and align expectations across stakeholder groups to ensure the effective integration of AI literacy in higher education.

Introduction

Ever since access to Generative Artificial Intelligence (GenAI) tools became widespread in the public domain, there has been a growing emphasis on its potential, challenges, and ramifications for the education sector (Yu & Guo, 2023). Although the practice of AI in Education (AIED), such as online intelligent education systems, learning analytics dashboards and web-based chatbots has a longer history (L. Chen et al., 2020a, b; Chen et al., 2020a, b; Holmes et al., 2019), discussions on the contextualisation of AIED use have garnered more traction in the last few years. This has enabled important paradigm shifts in AIED, transitioning from AI-directed and AI-supported constructs to AI-empowered settings, with learner agency increasing over the course of that transition (Ouyang & Jiao, 2021). In this context, two central concepts underpin this study: 'competent use' and 'ethical perception' of AI. Competent use refers to the ability to critically evaluate, collaborate with and effectively apply AI technologies, while ethical perception relates to how individuals interpret and respond to the ethical implications of AI in practice. These concepts form the guiding framework for the investigation.

Several publications have presented definitions for AI competency and literacy, although a unified basis has not yet been established (Mikeladze et al., 2024; Ng et al., 2021). An operational definition proposed for AI literacy is "a set of competencies that enables individuals to critically evaluate AI technologies, communicate and collaborate effectively with AI, and use AI as a tool online, at home, and in the workplace." (Long & Magerko, 2020). Competence in AI is also intertwined with computational and data literacy, and hence needs to be considered more holistically (Olari & Romeike, 2021). Although several AI competence frameworks have been proposed in the recent past (Sattelmaier & Pawlowski, 2023; Su & Yang, 2023; Tenório & Romeike, 2023), the differences in the underpinning approach for developing these frameworks, depending on whether they are conceptual models or derived from empirical data, result in considerable differences in the final output (Mikeladze et al., 2024). While this is not a criticism of these frameworks, it does result in varied and subtly nuanced perspectives of AI literacy and competency among students and staff (Alenezi, 2024; Chan & Hu, 2023).

Similarly, concerns around the ethical use of AI also manifest differently in these varied perspectives. Ethics is not detached from AI competency but rather is identified as one of the five key components that constitute the AI competency framework alongside technology, impact, collaboration, and self-reflection (Chiu et al., 2024). Within the healthcare sector, four key ethical challenges were identified: (i) informed consent for use, (ii) safety and transparency, (iii) algorithmic fears and biases and (iv) data privacy (Gerke et al., 2020). Similar challenges apply for disciplines beyond healthcare too (Stahl, 2021). Specifically for education, these translate into, bias and discrimination associated with automated scoring systems, surveillance or tracking systems that monitor students and/or staff, predictive systems adversely impacting student autonomy and privacy violations (Akgun & Greenhow, 2022; Kooli, 2023). In addition to these issues, ethical considerations around the use of AI and its impact on student assessment has also been the topic of many research publications (Martínez-Comesanã et al., 2023; Qadir, 2023).

While these studies help define common ethical risks, they also highlight the fragmented nature of ethical understanding within AIED, influenced by disciplinary traditions, stakeholder interests, and institutional contexts. This variability contributes to differing ethical perceptions among university staff and students. In a study conducted by (Farhi et al., 2023), a 55% variance was found in students' views on 'perceived ethics' on using ChatGPT for generating text and creative ideas (Malmström et al., 2023). While multiple studies have also surfaced a lack of awareness around ethical issues among staff and students (Ali et al., 2024; Braunack-Mayer et al., 2020), divisions in staff perception of ethical risks associated with AIED are very much present (Titko et al., 2023).

Therefore, with the literature revealing a lack of shared understanding among educators and students on what competent and ethical use of AI constitutes, the key objective of this research paper is to surface the similarities and divergences in opinion across these stakeholder groups on specific AI-based use cases or applications in a higher education context. Although high-level explorations of these topics have been presented in earlier studies, highlighting nuances at a more granular level—particularly through specific use cases—remains limited. Furthermore, a holistic consideration of GenAI tools, which accounts for the varying degrees of complexity of these tools, has seldom been included in assessments of staff and student opinion.

This study therefore adopts a use-case-driven approach, grounded in a conceptual understanding of competence and ethics, to provide a more focused and detailed examination of stakeholder perceptions. By analysing staff and student responses to these specific use applications, we aim to address the following research questions (RQs):

RQ1 What is the mutual understanding between university staff and students regarding the competent and ethical use of AI?
RQ2 What explains the variance in opinion among staff and students on the competent and ethical use of AI?

Methodology

This study was conducted as part of the 'Building AI Based Educational Languages' (BAIBEL) project at the University of Leeds, UK and was granted ethical approval by the University's Faculty Research Ethics Committee for Business, Environment and Social Sciences – reference number BESS+FREC 2023-0687-1075.

As part of the project, discussion workshops were held between January and March 2024 with key stakeholders in the higher education sector: (i) academic staff, (ii) technical and professional services staff, and (iii) students at the University of Leeds. A University-wide open call was circulated through e-mail and other community channels asking interested staff and students to register their interest for participation. Convenience sampling was used to select participants based on their availability and ease of access. The research participants included 25 academic staff, 34 technical and professional services staff and 27 students. At the start of the workshop, participants were invited to complete an anonymous questionnaire hosted on the JISC Online surveys platform. Three main themes were explored in the questionnaire: (i) participants' frequency of use of different AI use applications, (ii) which AI-enabled use cases participants perceived as AI competence and (iii) which AI-enabled use cases participants express ethical reservations for. The collected data has been analysed and presented in this paper. Although it is only the two latter themes that are central to our RQs, data on frequency of use was collected and analysed to provide broader context for our findings and to check for alignment with trends on AI use reported elsewhere.

To collect opinion on a range of AI-enabled tools, the questionnaire was designed to include a diverse mix of use applications. As stated earlier, the study aims to elicit staff and student opinion on competent and ethical use through the lens of these specific use applications. The use applications selected for this study were derived from those explored in two large-scale surveys: (Shaw et al., 2023) and UK's Higher Education Policy Institute (HEPI) survey (Freeman, 2024). The use cases included applications of text, image, and video processing for validation, comprehension or production purposes. Specifically, the following use cases were included in the questionnaire, where the last four can be classified as conversational GenAI (cGenAI) tools, and the rest as non-cGenAI tools:

- Spell checker on a word processor (Validation).
- Typing assistant to review and rephrase text (Validation & Production).
- PowerPoint 'Designer' feature offering suggestions for slide layouts (Production).
- Software that can edit images and videos automatically (Production).
- Conversational tool to brainstorm ideas (Comprehension & Production).
- Conversational tool to generate essays or writeups (Production).
- Conversational tool to generate tasks to support student learning (Comprehension).
- Conversational tool to generate tasks to support material/lesson development (Production).

In addition to selecting the use cases that they perceived as requiring AI competence, respondents could justify their choices through a free-text response, although this was not mandatory. Likewise, a free-text response could also be provided for the use cases that respondents flag for ethical concerns. Although the questionnaire was designed primarily to collect quantitative data, the free-text responses provided complementary qualitative data to draw deeper insights from the quantitative trends. Thereby, we are able to uncover the shared understanding and differences in opinion of what constitutes competent and ethical use of AI in the viewpoint of staff (academic and professional services) and students.

The qualitative analysis of free-text responses followed Braun and Clarke's six-step framework for thematic analysis (Braun & Clarke, 2006, 2012), informed by the principles of reflective thematic analysis (Braun & Clarke, 2019). Each dataset from the workshops was first analysed individually and independently by researchers, before being compared across the sites. Participant responses were synthesised to develop overarching trends, allowing for a collective analysis rather than treating individual responses in isolation. The findings are presented in a narrative format to preserve the context, flow and depth of participant responses. This approach allowed us to capture not only the key points raised, but also the ways in which ideas connected and were prioritised, reflecting the situated and holistic nature of participants' experiences. Furthermore, a standalone analysis of the qualitative data in terms of themes would be inappropriate in this context as the textual data was justification provided by the participants for their responses to the quantitative-style questions. As a result of this strong coupling to the quantitative data, qualitative responses are analysed from the perspective of eliciting the rationale for choices made by participants for what they classify as competent and ethical use of AI.

Pie charts, clustered bar charts and proportional Venn diagrams are used to show the quantitative findings on frequency of use, competent use of AI and ethical use of AI as expressed by the three stakeholder groups. Principal component analysis (PCA) is used to identify the key factors that underpin the variance observed in staff and student opinion on competent and ethical use. As a multivariate statistical method, PCA formulates a series of principal components (PCs), which are linear combinations of the original variables (in our case the different use applications identified in the questionnaire) that maximally explain the variance observed in the data. A more detailed explanation of PCA and the underlying mathematics can be found elsewhere (Bro & Smilde, 2014; Greenacre et al., 2022). Prior to subjecting data to PCA, tests for factor analysis, including the Kaiser–Meyer–Olkin (KMO) test and Bartlett's sphericity test, were performed using the 'factor_analyzer' library in a Jupyter Notebook using Python coding language.

Since PCA is affected by scale, data that satisfied the threshold requirements of the abovementioned tests was then standardised using the 'sklearn.preprocessing' package. PCA was performed on the processed data using the 'PCA' class from the 'sklearn.decomposition' module in Python. This allowed calculating the eigenvalues of PCs, the variance explained by each PC and the loadings of variables for each PC, which were used to develop Scree and Score plots. The former depicts the eigenvalues of all PCs while the latter is a scatter plot of the principal component scores (usually for the first two PCs for a 2-D graph). The graphs were generated using the 'matplotlib' plotting library in Python.

Results and discussion

Use of AI tools

Over 90% of all three surveyed groups declare using a spell checker 'often' or 'sometimes' on word processing software (Fig. 1). Although students report greater use of typing assistant software to review and rephrase text (41% say 'often' compared to 16% of surveyed academics and 12% of surveyed professional services staff), the use of PowerPoint's Designer feature is more common among staff (68% and 74% of academic and professional services staff respectively say 'often' or 'sometimes' compared to 49% of students). This is consistent with the type of outputs these groups typically produce – while staff often use PowerPoint slides for lectures and meetings, report writing is a frequently used student assessment approach across disciplines.

Although there are differences in how staff and students use these tools, the gap in frequency of use is larger for cGenAI tools than for non-cGenAI tools. For example, 82% of students surveyed reported using cGenAI 'often' or 'sometimes' to generate tasks that

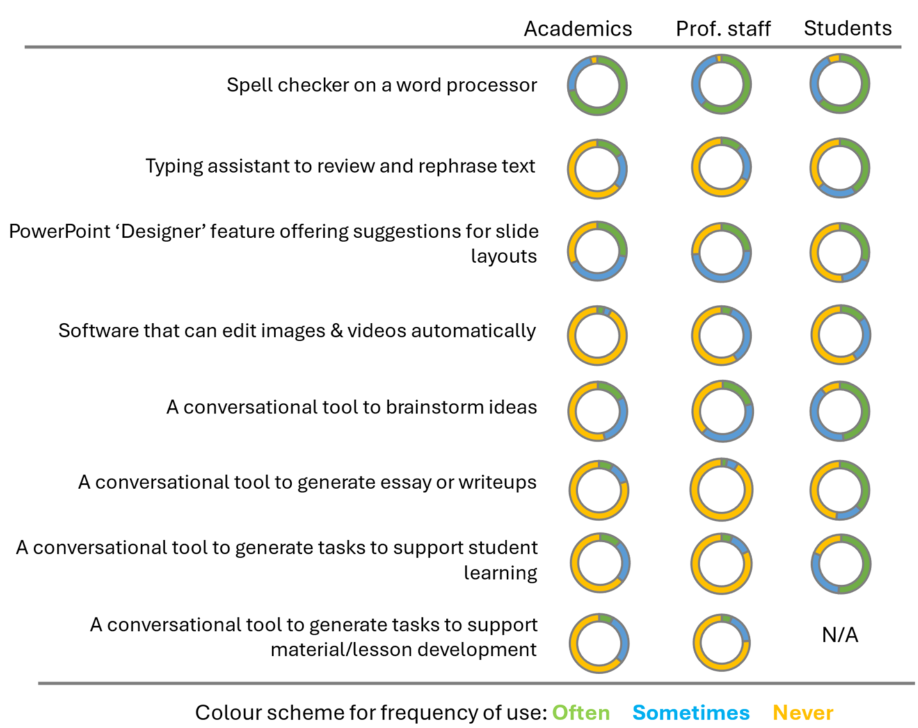

Fig. 1 Pie charts showing the frequency of use of different tools as declared by academic staff ($n=25$), professional services staff ($n=34$), and students ($n=27$) on a 3-point Likert scale: often (green), sometimes (blue) and never (yellow)

support their learning (Fig. 1). In contrast, only 36% of academic staff and 24% of professional services staff reported using cGenAI to generate tasks for developing teaching materials or lessons. These findings reflect results from larger studies that have also identified a significant difference in how staff and students engage with GenAI tools (Shaw et al., 2023).

Likewise, while over 50% of students report using cGenAI to generate writeups or essays, nearly 85% of staff report 'never' having used cGenAI for this purpose (Fig. 1). The divide persists even when it comes to using cGenAI for brainstorming ideas - the proportion of the student population that uses it 'often' (48%) is nearly three times that among academic staff (17%). Among academic staff, cGenAI is mainly used to brainstorm ideas and with occasional use for task development. In contrast, students use cGenAI more widely - not just to generate ideas or support their learning, but also to create essays or written work. It is important to note that when polling students, we did not ask specifically about their use of cGenAI for assessed work, but more broadly as part of their learning process. This might explain the higher proportion of student respondents declaring their use of cGenAI in our study compared to the UK-wide findings published by HEPI (Freeman, 2024).

Overall, 38% of professional services staff and 48% of academic staff declare 'never' using a cGenAI tool for any of the purposes mentioned in the survey – brainstorming ideas, generating tasks to support student learning or material/lesson development, or generating essays or writeups. Among students, this number was only 7%. While these numbers might not directly apply to other Universities and educational institutions, they unequivocally highlight the scale of the usage gap between staff and students. This gap could stem from several reasons – a greater fraction of staff being averse to change and students being early adopters, varying degrees of self-perceived competence in using AI, and differing perspectives of what ethical use of cGenAI constitutes (Chan & Lee, 2023). Should the 'frequency-of-use' gap arise from a fundamental competence gap because of lack of training or upskilling, appropriate action would be needed (Sperling et al., 2024). However, an individual could also use cGenAI less frequently despite having the competence for various other reasons. Therefore, we next explore staff and student perspectives of being competent and ethical users of AI.

Views on AI competence

Across both staff and students, the use of cGenAI tools is considered more favourably as AI competence compared to AI-enabled non-conversational tools. However, interestingly, a greater percentage of students than staff view non-cGenAI tools as AI competence – 56% students compared to 27% academics selected the use of PowerPoint Designer feature as AI competence (Fig. 2). A large majority of academics consider the use of cGenAI tools for different purposes as AI competence; this is often higher or at par with the percentage of students and professional services staff who view these as AI competence. This includes the use of cGenAI to generate essays or writeups, for which among the groups, students have the lowest percentage considering it as AI competence (70%) as opposed to academics (80%) and professional services staff (76%). Hence, although cGenAI-assisted writing processes have come under increasing scrutiny for assessment in higher education (Wang, 2024), we see that a large majority of our surveyed staff indeed consider such a use case as requiring competence in AI.

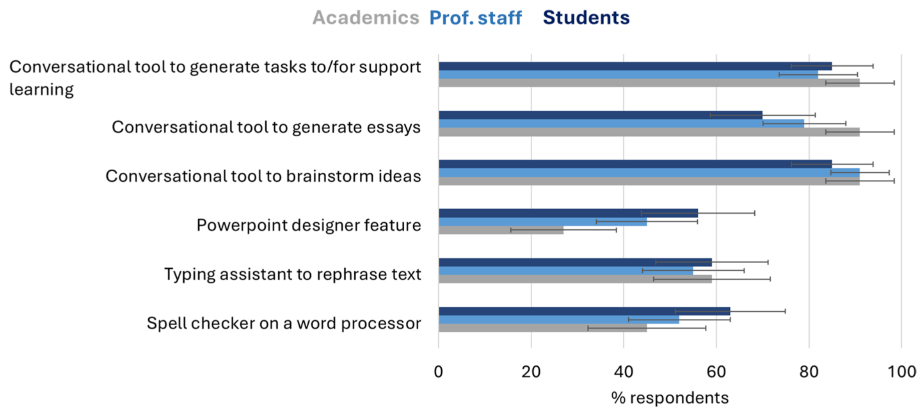

Fig. 2 Clustered bar chart showing the percentage of academic staff (grey), professional services staff (light blue) and students (dark blue) who consider each use application as AI competence. Error bars correspond to 80% confidence interval

Among academics, a few participants referred to the idea that simply using a tool for any purpose would not make an individual AI-competent; instead, competence would require a 'deeper understanding' (quotes below) and hence, they selected none of the use cases on the questionnaire as demonstrating AI competence.

> *I consider AI competence requires understanding of how the AI works, not simply using AI.*
> *I think a deeper understanding is needed for competence.*

There were no comparable opinions expressed by the professional services staff but some student respondents, who also considered none of the options as AI competence, justified this on the limitations of AI in producing a fully credible output:

> *I think there's still quite a gap in what can AI do. To me it is more of a tool to summarise text or to check if my theory is right. But I will never trust sources from ChatGPT etc. I will always obtain academic resources or information from an official source.*
> *Delegating parts of a skilful task to AI, without depending too heavily and entirely outsourcing tasks.*

On the other hand, there were participants across all groups who selected all the listed options as AI competence. From the reasoning provided, these participants appeared to have a less stringent definition of what competence constitutes:

> *They all involve generative output to varying degrees and therefore need checking and evaluation of output.' – Academic staff*
> *'I'd say any of these suggested activities all require a certain competence of understanding what the tool is assisting you with and employing it.' – Professional services staff*
> *'Because they all offer artificially generated assistance to complete different tasks' – Student*

Apart from these two extreme viewpoints, a significant fraction of participants define competence in AI through an inclination towards the cGenAI tools – these participants do not consider the use of a spell checker, typing assistant or PowerPoint's Designer feature as AI competence. This is, in part, because of access to cGenAI tools in the wider public domain being a more recent phenomenon compared to the other tools:

> *'I suppose the non-ChatGPT examples are embedded in existing programmes that I would not think of as requiring competence in AI to use. So, they might use some 'smart' tools, but they do not require specific engagement with an AI programme.' – Academic staff.*
> *'I suppose because the ones I haven't ticked seem more old-school. More like they are programmed, automated systems rather than actual 'intelligence'. I don't feel they learn - but are just told.' – Professional services staff.*
> *'The ability to use less common AI tools well show competence' - Student.*

The selective recognition of cGenAI use as a form of AI competence is not only due to the novelty of these tools, but also because they are perceived to require a higher level of understanding or skill to be used effectively:

> *'These applications go beyond automation of and after human input. These tools take human input and apply a higher level understanding to construct solutions to not only a given problem, but related and integral content as well.' – Academic staff.*
> *'These require more input from the user than spellchecker or Grammarly do. You would need to formulate a prompt, respond to the output, tweak etc. Compare this to the auto-suggestions from spellcheckers - here you get given a suggestion without asking, and just click accept or ignore.' – Professional services staff.*

With regards to the applications of cGenAI tools explored herein – (i) brainstorming ideas, (ii) generating essays or writeups, and (iii) generating tasks to support student learning or material/lesson development – we see a consensus across all surveyed groups that all three use cases constitute AI competence. As shown in Fig. 3, a proportional Venn diagram depicting the relative fraction of respondents in each of the intersections, 72%, 74% and 70% of academics, professional services staff and students, respectively regard all three use applications as AI competence.

Among the three surveyed applications, the case of generating essays or writeups could be considered as the one that produces an output closest to a finished product. In this context, the percentage of respondents who fall in the intersection of brainstorming ideas and task generation in the Venn diagram for AI competence are noteworthy – this fraction represents people who opine that while using cGenAI for brainstorming and task generation constitutes AI competence, using it for generating write-ups does not. Although this fraction is a minority in all three stakeholder groups (Fig. 3), the highest percentage is among students (11%), followed by professional services staff (9%) and lastly academics (4%). Hence, among our surveyed participants, students are most critical of classifying the use of cGenAI for generating essays as AI competence.

Views on ethical use

The most significant ethical concern raised by staff (academics and professional services) is regarding the use of cGenAI tools to generate essays or writeups with over 90% of respondents in both staff groups flagging this as an issue. Among students, although the majority concur (Fig. 4), the fraction of those in agreement is not as unanimous as that in staff, which can result in a tension between staff and students as reported by (Shaw et

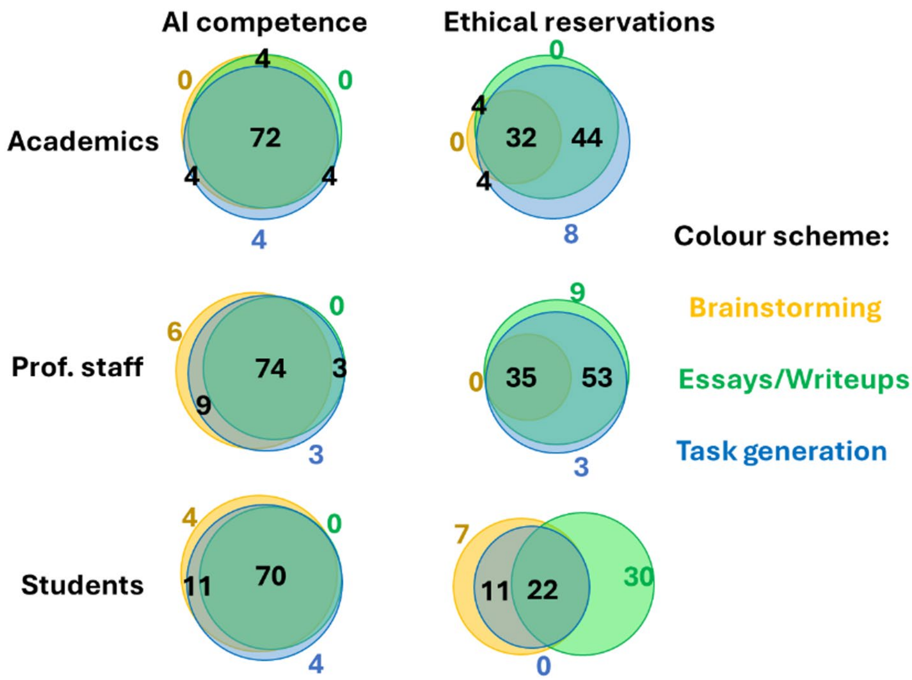

Fig. 3 Proportional Venn Diagrams showing the percentage of respondents in all three surveyed groups who consider the use of cGenAI for brainstorming ideas (yellow), generating essays/writeups (green) and task generation to support student learning or material/lesson development (blue) as AI competence (left) and percentage of those who express ethical reservations for the same use applications (right). The numbers displayed in black in the Figure correspond to the percentage of respondents who fall in the corresponding intersection regions. The numbers displayed in yellow, green, and blue correspond to the percentage of those who fall exclusively in the region of the three colour-coded use applications. Note that the sum of all displayed numbers will not necessarily add up to 100 as some respondents might have selected none of the use applications as AI competence or expressed no ethical reservations for any of them

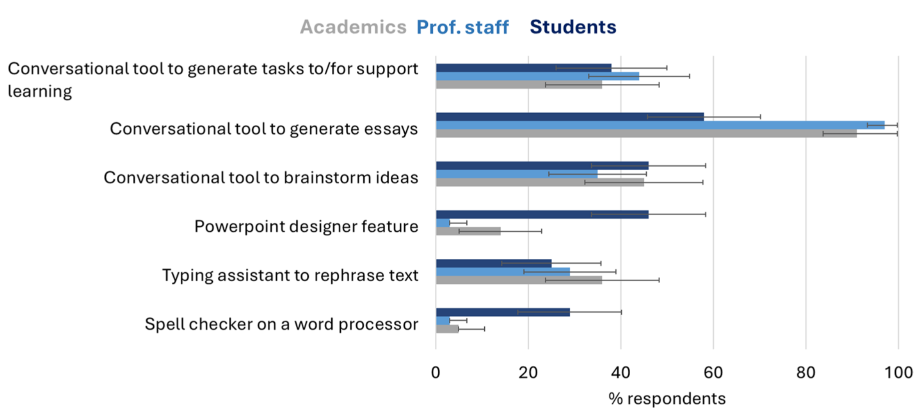

Fig. 4 Clustered bar chart showing the percentage of academic staff (grey), professional services staff (light blue) and students (dark blue) who express ethical reservations for each use application. Error bars correspond to 80% confidence interval

al., 2023). The main reason for flagging this use case as an ethical concern was academic integrity or misconduct i.e. an individual potentially claiming a cGenAI essay output, as generated or revised, as their own. This sentiment was evident in the comments provided by participants across all stakeholder groups:

> *'I feel these lead to us not knowing who produced the work- an AI system or a student.' – Academic staff.*
> *'There could be issues with academic integrity in terms of rephrasing or writing essays.' – Professional services staff.*
> *'We can't use AI to write essays, it's not our own thinking' – Student.*

Furthermore, staff concerns also stem from the opinion that using cGenAI for essays potentially disrupts the 'intellectual process' that informs writing practice, which is eventually detrimental to the student learning experience:

> *'Using generative ai to write an essay removes the intellectual process implicit in writing such as creating narrative, selecting sources etc. There needs be no independent or critical thought, which are things that should be present within the practice of writing an essay' – Academic staff.*
> *'Any use of technology that is being used to replace the process of learning or creating a new piece of work devalues the experience of the process and therefore the result.' – Professional services staff.*

Some students argue that creating high-quality essays with cGenAI takes significant effort and should not be seen as simply handing over the task to technology:

> *'Essay prompts generated from scratch is mostly quite bland and the specifying takes most of time to brainstorm.' - Student.*

The Venn diagrams on reservations against ethical use reveal interesting differences in opinion between staff and students. While 32% and 35% of academics and professional services staff respectively express reservations against ethical use of cGenAI for all three use cases, the equivalent number is 22% among students (Fig. 3). The reasons for this blanket reservation against cGenAI ranged from intellectual ownership and biases in data informing large language models to disingenuous use and non-transparency (quotes below), which are consistent with empirical studies done elsewhere (Olawale & Mutongoza, 2024).

> *'To use a specific example, concern that say, AI generated images are dominated by a certain ethnicity, demographic etc.' – Academic staff.*
> *'How do you ensure that in those uses, the user is clear with transparency and policy and guidelines?' – Professional services staff.*
> *'Depending on their purpose/use, these can be presented disingenuously as people's own work when they are not. It presents ideas/work as your own when in fact it was not your own ideas/work' - Student.*

Hence, although academic staff have previously been reported to be 'positive about using AI for information searchers and preparation of teaching materials' (Titko et al., 2023), we observe a non-negligible share of academics who express ethical reservations for such applications. Figure 3 shows that many members of staff are also concerned about the use of cGenAI for task generation to support learning or lesson/material development – 44% of academics and 53% of professional services staff express reservations against ethical use of cGenAI for both use cases but do not flag an issue about using it for brainstorming ideas. In contrast, there is no such demographic in the surveyed student population – 30% of students express concerns on essay/writeup generation, but none fall in the intersection of essay/writeup and task generation without having concerns on using cGenAI for brainstorming. These findings potentially point to students adopting a less critical stance on the ethical use of cGenAI compared to staff and brings to surface the differing boundaries in student and staff judgment on this issue – as noted in other research (Zhai et al., 2024). In our findings, going beyond ethical issues in assessment, staff also refer to bias *in* AI as a reason for why even using cGenAI for task generation could be plagued by ethical issues. While some students were aware of potential bias or inequitable access, from both STEM and creative disciplinary areas, overall, ethical comments were not as strongly evident in the student responses:

> *'Data harvesting; inbuilt racist, gender, linguistic etc biases of the AI; lack of intellectual ownership and independent creative production of the material generated; ecological disaster created by server farms;' – Academic staff.*
> *'I have some reservations about all AI given the source of the information in their datasets. Are they respecting copyright? Is the AI biased based on any skew in the information its dataset is based upon?' – Professional services staff.*

Divergences in opinion can also be observed for non-cGenAI tools. Although a similar share of students raised ethical concerns about using spell checkers and typing assistants (Fig. 4), academic and professional service staff were much more critical of typing assistants. Nearly 30% of staff expressed concerns, mainly because of issues around academic integrity and the difficulty of judging whether a piece of work was created by a student or by an AI system. As GenAI ubiquity takes hold, this remains a widespread issue for different disciplinary areas and HEIs at institutional level, prompting the urgent need to identify "robust assessment methods and educational policies that embrace GenAI usage while ensuring academic integrity and authenticity in assessments"(Ardito, 2024).

Variances in staff and student opinion on competent and ethical use of AI

In the preceding sections, we highlighted the similarities and differences in opinion of university staff and students on the competent and ethical use of AI. Although the analysis was useful to draw comparisons between groups and identify overarching trends, the underlying heterogeneity within groups was analysed only for specific cGenAI applications using Venn diagrams. In this section, we further explore the differences in opinion that exist among members of staff (academics and professional services staff) and students using the method of principal component analysis.

As a dimensionality reduction method, PCA transforms data to a form where the maximal variance is captured in a fewer number of newly constructed variables called principal components (PCs). In simpler terms, PCA simplifies complex data by identifying the main features while still representing the original data well. As explored in this study, we have opinion of 59 members of staff on 8 different use cases of AI (4 non-cGenAI and 4 cGenAI) and of 27 students on 7 use cases (4 non-cGenAI and 3 cGenAI). Prior to performing PCA, the suitability of the data to perform factor analysis was checked using the KMO and Bartlett's sphericity tests. The KMO value was above the minimum requirement of 0.6 indicative of adequate sampling for both staff-related data sets – 0.70 for staff opinion on AI competence and 0.66 for staff opinion on ethical use. Likewise, both data sets also satisfied the Bartlett's sphericity threshold of $p < 0.05$. However, for

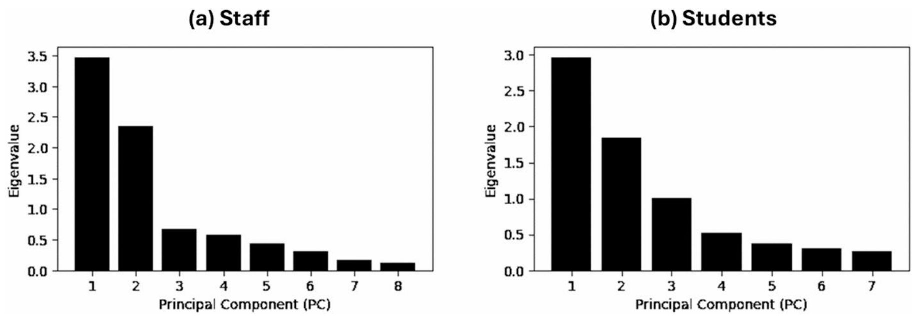

Fig. 5 Scree plot showing the eigen values of the PCs formulated for (**a**) staff and (**b**) student perspectives on considering different use applications as AI competence

Table 1 Principal component loadings for staff opinion on AI competence and ethical use and student opinion on AI competence

Use application	Staff – AI competence		Students – AI competence		Staff- ethical use	
	PC1	PC2	PC1	PC2	PC1	PC2
Spell checker on a word processor	-0.24	0.47	-0.08	-0.60	0.13	0.63
Typing assistant to review and rephrase text	-0.29	0.36	-0.34	-0.41	0.38	-0.06
PowerPoint 'Designer' feature offering suggestions for slide layouts	-0.32	0.46	-0.39	-0.41	0.27	0.48
Software that can edit images and videos automatically	-0.37	0.25	-0.33	-0.19	0.26	0.03
Conversational tool to brainstorm ideas	-0.43	-0.17	-0.46	0.28	0.44	0.05
Conversational tool to generate an essay	-0.35	-0.34	-0.44	0.33	0.14	-0.57
Conversational tool to generate tasks to support student learning	-0.40	-0.37	-0.46	0.28	0.47	-0.15
Conversational tool to generate tasks to support material/lesson development	-0.39	-0.32	N/A	N/A	0.51	-0.14

the student data sets, while the competence-related data was found to have a KMO value of 0.67, that of ethical use was 0.59, slightly below the minimum requirement threshold. Therefore, all data sets except for student opinion on ethical use was subject to PCA, results of which are presented below.

With regards to staff opinion on AI competence, Fig. 5(a) shows the results of the PCA (Scree plot) depicting the eigenvalue of each of the principal components. This helps identify the number of major non-random dimensions, which can be ascertained by locating the 'elbow' in the graph i.e. where there is an abrupt change in slope. Using this visual criterion, we see that beyond the first couple of PCs, the remaining can be considered as random dimensions. PC1 accounts for 43% of the variance in the data while PC2 accounts for 29%. Another approach to determine the number of significant PCs is by applying Kaiser's criterion, which sets the minimum eigenvalue for a PC to be significant as unity, using which we again find only the first two PCs to satisfy this criterion. Cumulatively, the two PCs account for 72% of the total variance in staff opinion on AI competence, and consequently, the corresponding PC loadings provide valuable information on the most important factors that contribute to the variance in staff consideration of AI competence. In simplified terms, this analysis has identified two main directions or features which explain the differences in perspectives of what staff and students consider as AI competence. From Table 1, we infer that the use cases with the highest magnitude loadings for PC1 are 3 cGenAI applications (ranging from – 0.43 to -0.39), while those that have the most impact on PC2 are the statements on spellchecker

(0.47) and PowerPoint designer feature (0.46). Furthermore, all the cGenAI applications have a negative PC2 loading value while the 4 non-cGenAI applications have positive PC2 loadings.

Figure 6(a) presents the Score plot, which is a scatter plot of the individual staff opinion on use applications they regard as AI competence, shown using the first two PCs as the coordinate axes. Although we started with as many as 8 use cases, PCA has helped effectively simplify the data set into just two dimensions without losing much information. This representation is particularly useful to identify clusters within the data and helps visualise the variation in what is and not considered as AI competence. The spread of points along the PC1 axis is typically based on the number of use cases being considered as AI competence: ranging from a PC1 value of -2.01 (associated with considering all 8 use cases as AI competence) to 4.64 (associated with considering none of the use cases as AI competence). On the other hand, PC2 accounts for the divide between cGenAI and non-cGenAI use cases, ranging from − 2.01 (for considering only the 4 cGenAI applications as AI competence) to 3.77 (for a skew towards the non-cGenAI use cases). Thereby, we identify five clusters of responses in the Score plot (Fig. 6(a)) – Cluster A (yellow) is reflective of respondents that barely consider any of the use applications as AI competence while Cluster B (blue) consider nearly all or most as AI competence. Cluster C (green) depicts staff who consider more cGenAI applications as AI competence than non-cGenAI applications while Cluster D (orange) is the opposite. Lastly, Cluster E (grey) represent responses that consider a couple of use cases from both categories as AI competence with no prominent skew towards either category of AI applications.

The PCA results of the student opinion data on AI competence share several similarities with that of the staff data. From the Scree plot (Fig. 5(b)), we see that the first two PCs are the most significant dimensions with PC3 only just about meeting Kaiser's criterion. In this case, PC1 accounts for 41% of the variance in the data while PC2 accounts for 25%. As was observed in the PCA results of staff data, the PC1 loadings for all factors are negative with the highest magnitude loadings being for the 3 cGenAI applications and the PC2 loadings switch signs between the non-cGenAI and cGenAI use cases (Table 1). Therefore, similar clusters can also be identified in the corresponding Score plot (Fig. 6(b)). Hence, although we surveyed up to 8 different use cases among staff and 7 use cases among students, PCA reveals that the substantial variance in staff and student opinion on AI competence can be captured by essentially two features – (i) the number of use cases that they consider as AI competence and (ii) the divide between the

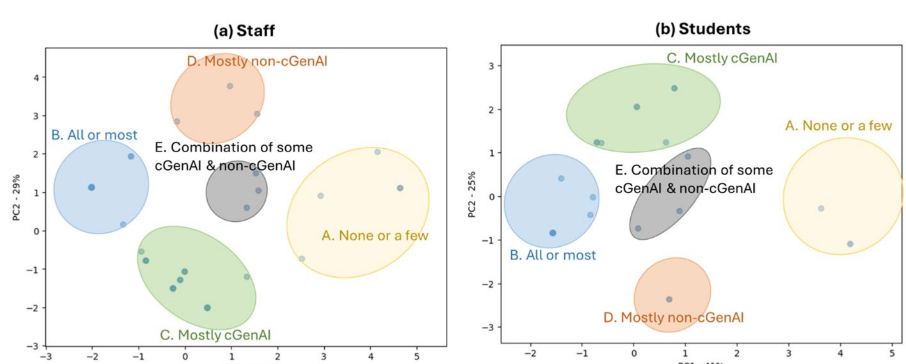

Fig. 6 Scatter plot of principal component scores of the first two components for (**a**) 59 University staff and (**b**) 27 student responses on use cases viewed as AI competence

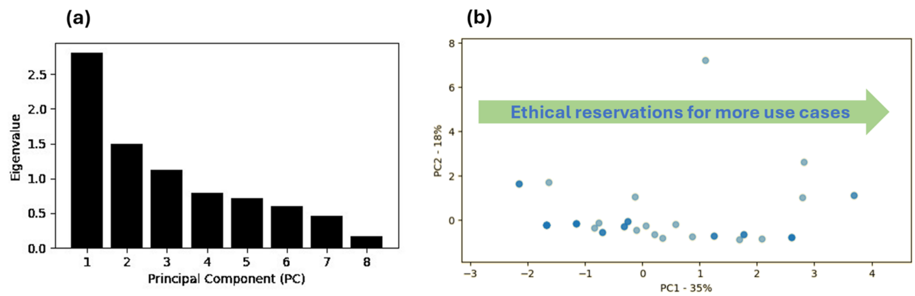

Fig. 7 (**a**) Scree plot showing the eigen values of the PCs formulated for staff opinion on ethical reservations for the different AI use applications and (**b**) Scatter plot of principal component scores of the first two components for staff responses on ethical reservations

non-cGenAI and cGenAI applications. Interestingly, these same two features were also surfaced in the qualitative data presented in Sect. Views on AI competence, where the differences in number of use cases identified as AI competence was attributed to varying stringency with which the term 'competence' was applied, while the divide between non-cGenAI and cGenAI applications was attributed to the novelty and a perceived higher level of understanding or skill required to use cGenAI effectively.

Moving onto staff reservations on ethical use, the Scree plot (Fig. 7(a)) reveals the first 3 PCs having an eigen value greater than one. Cumulatively, the first two PCs account for 53% of the total variance in staff opinion on ethical use of AI, which is comparatively lower to the 72% cumulative variance captured by the first two PCs for staff perspectives on AI competence. From the component loadings in Table 1, we see that the use applications with the highest loadings for PC1 are cGenAI for generating tasks to support material/lesson development (0.51), generating tasks to support student learning (0.47), and for brainstorming ideas (0.44). The feature with the next highest PC1 loading is the use of a typing assistant (0.38). As for PC2, it is a strong function of the following use cases: spellchecker (0.63), cGenAI for generating essays (-0.57), and PowerPoint Designer feature (0.48).

The corresponding Score plot using the first two PCs (Fig. 7(b)) does not have as clear a demarcation of clusters as observed in the plot for staff perspectives on AI competence (Fig. 6(a)). Nevertheless, from the knowledge of the relative PC1 loadings for the different use cases, we see that staff who express no ethical reservations about any of the use applications fall on the left end of the PC1 axis (PC1 value of -2.2), while those who flag most or all applications fall on the right (PC1 value of 2.6 to 3.7). Besides these two extreme viewpoints, respondents who only flag one specific application, such as essay/writeup generation or video/image editing software for ethical concerns have a PC1 value in the range of -1.6 to -1.7. Scatter points in the PC1 range of 1 to 2 are indicative of responses which express reservations against all use cases of cGenAI. However, staff perspectives on ethical reservations are quite diverse and although PC1 does a reasonable job in separating out extreme viewpoints, we observe several scatter points in the PC1 range of -1 to 1, which are not clearly separated on the PC2 axis either. This suggests a much more diverse and varied interpretation of ethical use in the perspective of university staff compared to their perspectives on AI competence. These findings from PCA are coherent with the qualitative comments provided by staff respondents, where ethical reservations were expressed on various grounds, ranging from data biases to copyright and transparency (Sect. Views on ethical use).

Conclusions

This study set out to surface similarities and differences in understanding among university staff and students regarding the competent and ethical use of AI tools. The dual focus on competence and ethics offers a comprehensive view of how diverse AI tools are perceived and utilised in higher education contexts. Furthermore, it addresses an important gap in the literature by providing a more granular analysis of stakeholder opinions. The results highlight a significant disparity in the use of AI tools between students and staff, particularly in the adoption of conversational GenAI tools (cGenAI). While students report extensive use of cGenAI for tasks such as learning support and generating essays, staff engagement with these tools remains limited and focused on brainstorming or task development. This usage gap may reflect differences in attitudes toward AI, self-perceived competence and ethical considerations.

With regards to what constitutes as AI competence, the findings reveal varied perspectives across students, academic staff and professional services staff. While cGenAI tools are widely regarded as requiring AI competence, this perception is less prevalent for non-cGenAI such as spell checkers or PowerPoint Designer, particularly among academics. Interestingly, a higher percentage of students than academics view the use of such non-cGenAI tools as AI competence, indicating differences in how each group defines and interprets AI interaction. A clear consensus emerged across all groups that using cGenAI tools for brainstorming, essay generation, and task creation demonstrates AI competence. However, students were more critical of classifying essay generation as AI competence, reflecting a more cautious stance compared to staff. While some participants advocated for a deeper understanding of AI to qualify as competence, others adopted a more inclusive perspective, recognising any interaction with AI tools as requiring some level of skill. These findings underscore the importance of addressing gaps in understanding and engagement with AI tools, particularly between students and staff. They also point to the need for clearer definitions of AI competence that reflect the complexities of both generative and non-generative AI tools, as well as the skills required for their effective use in educational and professional settings.

With respect to ethical concerns, the findings draw attention to concerns surrounding the use of cGenAI tools, particularly for generating essays or writeups, with over 90% of staff flagging such use as problematic. These concerns largely centre on academic integrity and the potential for cGenAI outputs to undermine intellectual ownership and critical thinking processes, which are essential to student learning and skill development. Students, while also raising ethical concerns, demonstrated less unanimity, with 58% expressing reservations about cGenAI for essay writing. These findings reveal an interesting intersectionality of competence and ethics: most staff classify the use of cGenAI for generating writeups as needing AI competence, but also express reservations on ethical grounds, while comparatively more students are critical in classifying the use case as AI competence in the first place but less critical about its ethical use. There is a broader critique from staff regarding biases inherent in AI systems and these systemic concerns were less prominent in student responses, which tended to focus on ownership and the representational use of cGenAI outputs. Overall, the findings echo similar research (Ardito, 2024) in emphasising the contrasting ethical boundaries between staff and students, which point to the urgent need for institutional guidelines and dialogue to address ethical concerns, clarify acceptable uses of AI tools and align expectations across stakeholder groups in higher education.

The PCA analysis highlighted distinct patterns and variations in staff and student perspectives on AI competence and ethical use. For AI competence, approximately 70% of variance in staff and student opinion could be attributed to two main factors: (i) the number of AI use cases considered as competence (indicative of the varying stringency in the definition of AI competence) and (ii) the distinction between cGenAI and non-cGenAI tools. In contrast, ethical concerns among staff were more varied and less structured. While the majority flagged cGenAI applications for task generation and brainstorming, there was less consensus on the other use applications. Concerns centred on issues such as intellectual ownership, data bias and tool transparency - reflecting the complexity of ethical considerations noted earlier in the qualitative data. While AI competence was relatively well-defined across groups, ethical concerns remain diverse and context-dependent, suggesting that addressing these variations is essential for effective integration of AI tools in educational contexts. Based on these findings, the following action points assume significant importance: (i) Conducting AI literacy workshops for staff and students, (ii) Making available clear AI usage policies distinguishing acceptable from problematic use and (iii) Communicating strategies for fostering ethical AI use in coursework-type assessments in higher education.

In summary, this study highlights the complex and evolving dynamics of AI tool adoption, competence and ethical considerations within the higher education context. While students and staff demonstrate differing levels of engagement and perspectives on what constitutes AI competence, the divide is particularly pronounced in ethical concerns, where staff adopt a more cautious stance compared to students. The nuanced findings from the PCA analysis further emphasise the heterogeneity within these groups, with varying preferences and reservations shaping their views. These insights point to the need for targeted training, clear institutional policies and ongoing dialogue to bridge gaps in understanding. For instance, targeted training could include dedicated AI literacy workshops for both students and staff, focused on upskilling competence in the ethical and effective use of emerging GenAI tools. Institutional policies should clearly differentiate acceptable and unacceptable uses of AI, providing guidelines for transparency in academic work and assessment. In parallel, rethinking assessment practices - for example, through the use of reflective accounts, process-based submissions and oral examinations - could help reduce reliance on AI-generated outputs and better evaluate individual learning. Together, these actions can help bridge both competence and ethical divides, ensuring that AI is integrated thoughtfully into higher education. By addressing these challenges, institutions can navigate the opportunities and risks presented by AI in education with increased confidence and equity.

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Authors' contributions
MR and KK conceptualised the project and obtained resources. All authors contributed to the design of the survey questions. MR led the analysis of the data. MR, CW and KK wrote the first draft of the paper. All authors reviewed the manuscript and approved the submitted version.

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Data availability

The data informing the findings reported in this paper may be obtained on reasonable request from the corresponding author, subject to data sharing practice allowed in line with the ethical approval given for this project.

Declarations

Competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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