The new Invisible (service) Workers? AI, Emotional Labour, and Neurodivergent Academic Experience

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Inger Mewburn, The Australian National University
Karen Oakley, University of Canberra
Alice Richardson, The Australian National University

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Abstract

Use of artificial intelligence (AI) is increasingly becoming normalised in higher education, for better or for worse. While much has been written about AI's ethical challenges and transformative potentials, its capacity to create a more equitable academic workforce remains a largely uncharted territory. This paper explores AI as a potential tool for promoting equity among neurodivergent academics as they navigate the 'metricisation' of academic life (Burrows, 2012), where measures of productivity are attached to the value of individual workers. We explore this through data gathered from a large-scale international survey of academics (n=1234), which included PhD students and featured a substantial proportion of neurodivergent (ND) respondents (30%).

We analysed and compared 1) patterns of AI adoption, 2) affective relations to the technology and 3) perceived value for academic work in neurodivergent and non-neurodivergent academics. While all academics (including PhD students) reported similar frequencies and types of AI use, significant differences emerged in terms of affect and perception of value. Our findings suggest that AI's equity potential may lie not primarily in cognitive offloading—as commonly assumed—but rather in mediating emotional labour demands that disproportionately affect neurodivergent academics. This reframing has important implications for institutional AI policy development, human resource management practices, and the design of academic professional development. The study contributes to broader discussions about technological tools as equity enablers within increasingly pressurized academic environments characterized by intensified publishing expectations and teaching responsibilities.

Introduction

Artificial intelligence (AI) tools can easily be integrated in academic work have triggered fierce debates over assessment and student cheating (Evangelista, 2025). The controversy about AI as cheating has now spilled over into staff use, with students starting to demand their tuition fees back after finding out their teachers are using the technology (Rosenbaum, 2025). Academics turning to AI for help with large workloads should not surprise us: they are a group of workers under extreme pressure. For over 20 years now, many higher education institutions have been encouraged to function more as corporate-like entities; with transparency, accountability, and financial outcomes being privileged above traditional academic values (Strathern, 2000). Academic work is now continuously monitored and evaluated through quantitative indicators—publication counts, grant income, teaching evaluations—creating what might be termed a 'metrified subjectivity' where scholarly identity becomes inseparable from measurable outputs (Burrows 2013; Kenny, 2017). The consequences of this shift are evident in the increased workloads, psychological distress, and profound sense of alienation reported by academic staff across institutions (Gill, 2010).

Against this dark background, on November 30, 2022, so called Generative AI ‘entered the chat’ via the launch of ChatGPT from OpenAI. Since then, a plethora of AI tools have begun to emerge for many dimensions of academic work, from drug discovery to drafting emails. Whether AI will make humans obsolete, be a force for liberation from the mundane realities of academic life or just another cog in the machinery of academic overwork remains an open question. This paper explores the challenges and potentials of AI from the point of view of neurodivergent (ND) academics: might AI serve as a mechanism for advancing equity?

Neurodivergence (ND) is an umbrella term for a range of cognitive variations that diverge from what is typically considered 'neurotypical,' including but not limited to autism, ADHD, dyslexia, dyspraxia, Tourette syndrome, and other atypical ways of processing information, perceiving the world, and interacting with others. Many academic papers state the rate of neurodivergence to be approximately 15% to 20% of the global population, but the source of this statistic is not grounded in a specific empirical study. We launched the ‘Critical examination of academic work study’ in mid 2024 to try and find out how prevalent neurodivergence was in academia and how neurodivergent academics experienced academic work compared to colleagues who did not report a neurodivergent identity. This large-scale international (n=1234), surveyed a wide range of academics currently working in universities, including PhD students, but not administrative staff. 30% of the survey participants reported a neurodivergent identity. Without additional validation it is impossible to say whether or not neurodivergence is double the rate in academia as it is in the population as a whole, but it does suggest that universities should pay more attention to the needs of this cohort.

ND academics have reported facing significant additional challenges in the metricised university, putting them at increased risk of stress and burnout (Jones, 2023; Lambert & Harriss, 2022). For ND academics, the structural challenges of our neoliberal managerial style universities present extra challenges and barriers to opportunity. For example, ND academics can experience feelings of loneliness and marginalisation (Dwyer et. al., 2021), and yet not reach out for help because they feel reluctant to disclose, for fear of stigma, judgement and lack of career advancement (Tan et al, 2025). AI does not bring its own agenda to a conversation or request, and so might be a boon for ND academics struggling with the demands of university life. In this paper we explore what AI might offer ND academics in their work.

It is hard to know what to make of AI as a tool: part digital trickster, part tireless sidekick, and possibly both saviour and destroyer of (academic) worlds.

On the one hand, the integration of artificial intelligence into academic practice offers a compelling vision of liberated scholarly labour, where the most tedious aspects of research and teaching might be delegated to digital systems (Butson & Spronken-Smith, 2024). This potential for automation extends far beyond mere efficiency gains, suggesting a profound recalibration of researchers' relationships with their own intellectual production (Dai, 2023). By automating the more laborious elements of literature reviews, for instance—what one participant McDonal et. al (2024) described as the "most tedious aspect" of research—AI promises to shift the intellectual workload toward higher-order thinking and conceptual exploration. This capacity for delegation extends across numerous academic activities: processing literature, refining writing tasks, handling qualitative data analysis, streamlining peer review processes, catalysing creative ideation, and even assisting with tasks made more challenging by language issues (Hadan et al, 2024) disability, such as Dyslexia (Oviedo-Trespalacios, 2023). What emerges from this positive framing is the tantalizing possibility that AI might serve as a kind of "personal assistant" for the modern scholar, a privilege which has long disappeared from academic life, even though it was barely noticed in the first place[1]. By automating routine administrative work, there is the potential to create space for the aspects of academic life that most academics claim to enjoy most: teaching and research. AI may be a potential path toward reclaiming the intellectual core of academic work from the encroaching demands of administrative burden. We could, perhaps, imagine a scholarly landscape where academics are freed to engage more deeply with the generative, creative, and critical dimensions of their practice—precisely those elements that arguably remain most distinctively human and most central to the university's traditional mission.

On the other hand, the integration of artificial intelligence into academic practice casts a significant shadow which some argue threatens to undermine the very foundations of scholarly work (Ivanov, 2023). These concerns stretch far beyond simplistic worries about plagiarism, extending to profound questions about what constitutes authentic intellectual labour (Butson & Spronken-Smith, 2024). Perhaps most troubling is AI's potential to fundamentally disrupt established methodologies and ethical paradigms that have long guided research communities, especially if use is not disclosed (Hadan, 2024). As one academic in McDonald et al (2024) observed, delegating writing decisions to AI can "reduce human authors' sense of ownership," potentially leading to irresponsible assertions and a disturbing disconnect from scholarly responsibility. The limitations of AI-generated content—in particular the risk of incoherent logic, false descriptions, and what is aptly termed "hallucination"— are, to some extent, built into the very fabric of the technology, raising serious questions about knowledge integrity (Sekrst, 2024). The 'black box problem' has become a generic way of talking about out of control systems (Karasinski & Candiotto, 2024), but the fact remains that the very inscrutability of the algorithms underlying the smooth surfaces of this technologies makes them frustratingly opaque to researchers concerned with rigour and truth. Beyond these technical shortcomings, the most profound anxieties centre on AI's potential to erode essential human capabilities—writing, critical thinking, creativity—that many academics view as central to their professional identities (Octaberlina, 2024). The feared result is not merely reduced quality of academic outputs but a gradual "drought of human creativity and critical thinking" that strikes at the very heart of educational purpose. These concerns are not merely speculative but reflect emerging realities where AI integration creates new inequities and surprisingly increases workload as academics find themselves spending additional time detecting and addressing students' AI-generated submissions of questionable quality and originality (Bin-Nashwan et al, 2023).

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[1] In the vast literature on universities and their work, there is precious little written about the role of administrative assistants, typists, librarians and clerks. From the early 20th Century, these roles were more often than not 'womens' work'. (Szekeres, 2004) in "The Invisible Workers" notes the neo-liberal turn caused a quiet revolution in the nature and purpose of this work too; academics now sort their own (e)mail. Indeed, there is a long history of academics ignoring the 'hands" that help with menial academic labour (see also Sharpin, 1989). If AI slips into this invisible worker role, is it likely its traces will also disappear? If history is any guide, the answer must be yes. Part of the rationale for this paper is to capture emerging AI practices early in the development and preserve it for future history.

Through analysis of our survey data, we interrogate whether AI tools could potentially mitigate the "double workload" that many neurodivergent academics carry. Many excel in their disciplinary expertise while simultaneously navigating environments structured around neurotypical norms (Authors, under review). Navigating institutional bureaucracy, managing social interactions, and masking neurodivergent traits within neurotypical environments can exact a profound cognitive and emotional toll for neurodivergent academics, work which often remains unacknowledged within academic evaluation frameworks. Many neurodivergent academics report investing significant energy in interpreting social cues, processing sensory-rich environments, and adapting communication styles to meet neurotypical expectations—energy that might otherwise be directed toward intellectual pursuits (Tan et al., 2025; Dwyer et al., 2022).

This paper examines how AI technologies might specifically address this hidden labour dimension of neurodivergent academic experience at work. We argue that thoughtful integration of AI into neurodivergent academics' working practices could represent not merely an accommodation but a genuine advancement toward more equitable academic structures—provided the ethical risks are appropriately managed. These findings are offered with the aim of understanding when and where these tools might advance (or not) an equity agenda.

To that end, this paper poses three, inter-related questions:

- Do neurodivergent people report different rates of using AI compared people who do not identify as neurodivergent? If there is no difference, are there any other bio-demographic factors that are connected with higher or lower use (ie: gender, age, etc).
- Do neurodivergent and non-neurodivergent people use AI differently, if so how?
- Is there any difference between the way neurodivergent and non-neurodivergent people perceive the role and value of AI in their work?

We use a statistical analysis to answer question one about rates of use. To answer questions two and three, we use qualitative coding methods, including a basic content analysis to identify themes, a gerund analysis to explore processes and values coding of open text data, all described by Saldana (2021). We present our results, the limitations and a discussion of the implications before closing with a process note describing use of AI to produce this paper.

Method

Data for the 'critical examination of academic work' study was collected between June 2024 and May 2025. The dataset represents survey responses from 1234 participants after data cleaning, reduced from an initial 1,548 responses through the removal of ineligible participants, false starts, and incomplete submissions.

The survey collected comprehensive bio-demographic data from across six global regions. Respondents provided information on age (categorized from 18-24 to 75+ years), gender identity (male, female, or other), and academic discipline (classified into STEM, HASS, Design and Creative Arts, Business, or Unknown). The survey captured respondents' research student status, primary type of academic work, and presence of chronic conditions or disabilities. Additionally, participants reported on neurodivergence status (ranging from formal diagnosis to absence), caring responsibilities, perceived representational equity in their workplace, and financial security. This rich demographic profile enables examination of how diverse personal characteristics and circumstances may influence academic work experiences, including technology adoption patterns and work-related challenges, while

reflecting the survey's attention to inclusivity considerations beyond traditional demographic categories.
The survey explored various dimensions of academic work experiences, in summary:

1. **Employment and Study Status**
    - o Research student enrolment status
    - o Primary type of academic work performed
    - o Working hours and preferences
2. **Personal Circumstances**
    - o Presence of chronic conditions, disabilities, or illnesses
    - o Caring responsibilities
    - o Neurodivergence (with various levels of diagnostic certainty)
    - o Financial security
    - o Perceptions of representation within the workplace
3. **Working Patterns and Environment**
    - o On-campus work frequency
    - o Work hours
    - o Perceptions of PhD difficulty (past or present)
    - o Self-organization and efficiency
    - o Email management
4. **Academic Community and Networks**
    - o Sense of value within the university community
    - o Sense of belonging
    - o Professional network effectiveness
    - o Work autonomy
5. **Wellbeing and Work Experience**
    - o Work enjoyment
    - o Focus and concentration challenges
    - o Feelings of overwhelm
    - o Work-related exhaustion
6. **Technology and Environment**
    - o Generative AI usage and utility
    - o Productivity in shared spaces
    - o Campus work environment suitability
    - o Technology distractions
    - o Emotional responses to interruptions

The survey included two closed questions focused on Generative AI use in academic work. The first question asked: "I have used Generative AI in my academic work (eg: ChatGPT, Claude, Poe or some other large language model)". Response options were: Yes, No, I haven't tried any yet / don't have access, No answer. The second question asked: "I find Generative AI useful to my work (we are defining research degree study as work)". Response options were on a 5-point Likert scale): Strongly disagree, Disagree, Neither agree or disagree, Agree, Strongly agree. An open text question invited participants to share how they were using the technology in their academic work.

This data has some limitations, which will discuss in the conclusion, however the number of responses, especially the large number of people who disclosed a neurodivergent diagnosis, makes it an interesting data set for preliminary exploration of the potentials of AI use by neurodivergent people.

Results
Participants

Of the 1234 participants, 30% identified as neurodivergent (either having a formal diagnosis, or self-diagnosis or seeking diagnosis), 21.9% indicated that they were unsure if they identified as neurodivergent and/or had some traits. 47.9% responded that they did not identify as neurodivergent. 0.5% did not wish to disclose whether they were neurodivergent.

76.4% identified as female, 19.2% as male and 4.4% identified as either non-binary or did not wish to disclose their gender identity. The majority of participants were aged under 55 years (83.1%; 18-34 years = 25.4%, 35-44 yrs = 31%, 45-54yrs = 26.7%). Participants were predominantly from Asia Pacific (61.7%), with 27.6% from Europe and 10.8% from other regions (including Latin America, North America, Middle East and Northern Africa (MENA) and Africa). 31.8% reported having a chronic condition, disability or illness and 45% reported having caring responsibilities. 59.1% were enrolled as a research student[2]. The majority of participants were in research roles (including as students; 59.5%) or teaching roles (32.7%) with 7.7% in administrative or management roles 2.7%.

This section has results pertinent to each of our three research questions. We follow these results with a discussion of the implications of our findings.

Do neurodivergent people report different rates of using AI compared people who do identify as neurodivergent?

Approximately half of participants indicated that they use generative AI for work (n=604, 49.1%). 40% indicated that they do not use it for work (n=492 and 10% indicated that they either have not tried or do not have access to AI for work (n=123). 11 participants (0.9%) indicated they did not wish to disclose whether nor not they use AI for work; these participants were removed from further analyses. Of those using AI, the majority (66.4%) found it useful.

Pearson Chi square analysis revealed that there were no significant differences in reported rates of using AI for academic work between neurodivergent participants, those who identified as having traits or being unsure if they are neurodivergent and those who do not identify as neurodivergent (X2 (1215, 2) = 5.44, p=0.064). There were also no differences between groups in their ratings of the usefulness of AI for work (Fisher-Freeman-Halton Exact Test (597) = 9.58, p = 0.29).

Binary logistic regressions were conducted to examine predictors of use of AI for work. Two stable predictors emerged:

- Age: (Wald (1155, 3) = 12.93, p = 0.005). The odds of those aged over 55 years using AI were 37% less than those aged 35-44 years (OR = 0.63, 95% CI = 0.44-0.90 p = 0.011).

- Type of work: (Wald (1155, 2) = 7.58, p = 0.023). The odds of those in teaching and administration/management roles using AI were 34% and 64% more respectively than those in research roles (OR = 1.34, 95% CI = 1.03-1.74, p = 0.029 & OR = 1.64, 95% CI = 1.04-2.60, p = 0.033 respectively).[3]

[2] Since the majority of active research work in most universities is carried out by research students, we felt it was important to invite them to the survey and include them in the analysis. Since PhD students hold many Teaching Assistant (TA) positions, they are highly likely to be contributing significantly to the overall productivity of the university. We therefore classified them for the purposes of this study as workers as well as students.

[3] Binary logistic regression conducted initially entering all variables except for financial stability as this was highly correlated with age (lower age groups had lower financial security but higher use of AI).

General linear modelling (GLM) was used to determine predictors of finding AI useful. With all variables except financial security entered into the model, three significant predictors emerged:

- Working more than 40 hours a week ($F(1,504) = 8.93$, $p=0.003$ partial eta squared = 0.016); this was a negative relationship; less frequently working more than 40 hours a week leads to finding AI more useful.

- Finding distractions stressful or anxiety provoking ($F(1,504) = 13.45$, $p <0.001$, partial eta squared =0.024); there is a positive correlation between finding distractions stressful or anxiety provoking and finding AI useful.

- Finding technology distracting ($F(1,504) = 3.93$, $p = 0.048$, partial eta squared =0.007); this was a negative relationship indicating that those who find technology more distracting find less AI useful.

Do neurodivergent and non-neurodivergent people use AI differently, if so how?

The only other large-scale survey of academic workers' use of AI is McDonald, Hay, Cathcart, & Feldman (2024). They found that staff in Australian Universities (including professional staff) utilized AI tools across various professional activities. Workers in university reported the following use cases: administrative work, editing text, converting between one language and another, creating images, coding, teaching activities, generating ideas, literature work and data analysis.

An initial scan of the responses to 'how do you use AI' open ended questions with MaxQDA tailwind suggested the same categories dominated our sample. We used a content analysis on a modified version of the McDonald, Hay, Cathcart, & Feldman (2024) report, breaking the usages down into four main categories of academic work: Writing, Teaching, Research and Administration. We then coded all the data by hand and compared usage between the ND and non-ND cohort.

Findings of the content analysis are shown in Table 1: *Content analysis of AI use*, below.

Type of work	Number of respondents who mentioned this use case		
	Neurodivergent (n=370)	Non-neurodivergent (n= 864)	Difference (p-value)
Didn't use AI	188 (51%)	422 (49%)	+2 (p = 0.5677)
Did use AI	182 (49%)	442 (51%)	+2 (0.5677)
Writing (including	117 (64%)	199 (45%)	+17 (< 0.0001)

Entering of variables in different orders and a Wald Forward and Backward entry method were used to confirm significant variables, with the results presented from these the final models from the forward and backward entry.

ideation, editing, translating)			
Teaching (including curriculum development, marking, learning design)	62 (34%)	130 (29%)	+5 (0.2939)
Research and analysis (including data analysis, literature searching and coding, etc.)	118 (65%)	212 (50%)	+15 (0.0001)
Administration (including emails, routine reports, emails, etc.)	80 (43%)	123 (28%)	+16 (0.0001)

Table 1: Content analysis of AI use

This content analysis showed that the only area where ND and non-ND academics used AI roughly the same amount was to support teaching work. Neurodivergent academics were much more likely to use AI for Writing tasks (+17%), Administration (+16) and Research (+15). This analysis shows that when ND academics do use AI, they are more likely to use it for more than one purpose.

This analysis suggests that the ND academics in our sample were, perhaps, more curious and interested in what AI had to offer their workflow. The findings also suggest that ND academics were more likely to explore the affordances of AI and 'tinker' with the technology to achieve their desired outcomes. We were interested to see that ND academics differed so much in tasks that involved writing (most administrative tasks were writing focused). All writing involves 1) high levels of executive function, especially memory and focus, and 2) a theory of mind of the reader (Jurecic, 2007). Both executive function and theory of mind are both areas reported by ND as being more of a struggle in their work life. We will develop these ideas further in the discussion section.

Is there any difference between the way neurodivergent and non-neurodivergent people perceive the role and value of AI in their work?

Exploring the perceptions of AI in this text data was harder. Most of the text snippets people supplied in the open-ended survey text box were brief, however the number of replies (n= 581) makes a relatively large and varied data set. We began with a values coding analysis, based on Saldana (2015), where we examined the values, attitudes and beliefs about AI suggested in the responses. The majority of people only shared instrumental uses of the technology: naming tasks and tools. However, a significant number of AI users (n=191 / 30%) provided longer responses, which described aspects of their relationship with the tools. These responses were tiny windows on to their lived experience; providing a glimpse into the way they were 'living' with AI at work as a kind of 'companion'.

There was a difference in the number of ND (n=56) and non-ND (n=135) people in the number of people that reported using AI as a kind of companion at work. However, this split reflects the overall cohort, meaning that ND and non-ND were just as likely to report using AI as a companion. Given this similarity, we were interested to see if the two cohorts leveraged this companionship relationship differently. To explore this further, we did a thematic analysis of these responses, to try and identify a typology of AI companionship. We found six distinct types of companions, which are explained in the table below. Some people saw AI as just a singular type of companion, but most seemed to be framing AI as more than one kind of companion, reflecting the multi-dimensional use case of most AI tools, particularly chatbots.

An analysis of the companion types, numbers of reported uses, and some pull quotes to illustrate each type, are in Table 2, *Types of AI companions*, below:

Companion type	**Description (these were generated by MaxQDA Tailwind AI assistant)**	**Number of responses and percentage total from each cohort**		**Pull quote examples**
Colleague	Generative AI has become an integral part of the research and writing process, serving as a cognitive companion that helps them overcome challenges, explore ideas, and improve the quality of their work. The relationship appears to be more peer-like than simply a tool to be used.	Total: 139 ND: 35 (25%) Non-ND: 105 (75%) No significant difference between cohorts	Cohort size 182, 442 Proportions for the test: 35/182 = 19%, 105/442 = 24% Difference -5% p = 0.2602	Using AI as a “sounding board” or "bouncing ideas off". To organise thoughts "get my ideas into order" or to improve the quality of their ideas, particularly for writing: "elevate my writing and formulating overarching narratives" or to ‘untangle’ their initial thoughts and get them into order “I can get very caught up in small minor details (syntax, grammar, diction) and struggle to get my ideas down on "paper", so I use AI to express my ideas”
Assistant	Leveraging generative AI tools to augment and assist	Total: 98 ND: 29 (30%)	Cohort size 182, 442	Includes mundane aspects of research production: “As a kind of rudimentary

	them in their academic work, much like they would use a human personal assistant, research assistant, or collaborator. The AI is serving as a supportive partner in their research and writing processes.	Non-ND: 69 (70%) No significant difference between cohorts	Proportions for the test: 29/182 = 16%, 69/442 = 16% Difference 0% $p = 1.0$	research assistant, helping me to find or summarise relevant information"; and for writing involved in navigating institutional work, e.g.: "writing administrative texts (e.g. common emails)"
Librarian	Using the AI tools more as a knowledge repository - to summarize papers, find relevant literature, provide overviews of topics, and generally deliver curated information packages to support their research. Here, the AI is serving as an information retrieval and synthesis service.	Total: 48 ND: 13 (27%) Non-ND: 35 (73%) No significant difference between cohorts	Cohort size 182, 442 Proportions for the test: 13/182 = 7%, 35/442 = 8% Difference -1% $p = 0.8687$	Asking for advice on known topics, eg: "asked how to improve productivity (e.g., new technologies, software and hardware)"; "To do a quick scoping review as to current knowledge in a field" or asking for help with a specific (difficult) task, e.g.: "I like to ask Claude questions about statistics, much more useful and quicker than Google or a textbook"
Service dog	When AI tools are seen as a valuable "assistant" that can help ND academics overcome the unique challenges they face, much like how a service dog can help a person with a disability.	Total: 35 ND: 23 (66%) Non-ND: 12 (34%) Very significant difference between cohorts ND and non-ND cohorts (ND folks +36)	Cohort size 182, 442 Proportions for the test: 23/182 = 13%, 12/442 = 3% Difference +10% $p < 0.0001$	In these segments, AI tools are variously described as "life savers," "cognitive body doubles," and "well-being companions". Sometimes AI is explicitly framed as an assistive technology: "… sometimes when I don't feel like typing because a computer screen makes my brain hurt I will hand write my notes and

				get ChatGPT to transcribe them into text…”
Motivator	AI being used as a motivational tool that can help people stay engaged, focused, and productive, particularly when faced with challenges, like procrastination and ‘blank page’ anxieties.	Total: 41 ND: 15 (37%) Non-ND: 26 (63%) Some difference between ND and non-ND cohorts (ND folks -7)	Cohort size 182, 442 Proportions for the test: 15/182 = 8%, 26/442 = 8% Difference +2% p = 0.3663	As a conversational / sparring partner: “to get my creative juices flowing, help me focus my writing”; a way to get started when uncertain: “I get ideas for starting an argument when I am feeling overwhelmed”
Imagined Ideal Student	Using the AI system as a proxy or stand-in for their actual students, in order to get a sense of how the students might approach and respond to the academic's own course materials and assessments.	Total: 5 Very small number of responses so a comparison would not be that meaningful.	I would say group proportions suppressed for confidentiality too	To model what students might do: “I also use it to enter in my assessment tasks to see what students' responses/essay might look like” or how they might use AI, as a cheating protection measure: “To check whether it is capable of answering assessment tasks for students”

Table 2: Types of AI companion

The most outstanding difference in this table is the greatly increased likelihood of ND people to report using AI as a kind of ‘Service Dog’ to help them deal with a workplace geared around non-ND preferences. Interestingly, non-ND people were slightly more likely to look to AI as a Motivator, to help them overcome procrastination and stay focussed on task. A further examination of responses about AI as *Motivator* showed that non-ND people tended to talk about the AI-*Motivator* in instrumental terms as a kind of ‘lively tool’ that could help them keep up with the pace of their work, while ND people used more emotional language, which coded the *Motivator* as a wellbeing or mental health support.

As most people reported more than one type of ‘companion’, we did a simple code co-occurrence analysis to see what combinations were most popular. No-one reported using all of the identified AI companion types together, although combinations of two or more were reported by 80% of people. ND people were more likely to report combinations than non-ND people. The most common five most combinations reported were:

1. *Colleague* + *Assistant* (n=42)
2. *Colleague* alone (n=35)
3. *Colleague + Librarian* (n=15)
4. *Assistant + Colleague + Librarian* (n=12)
5. *Colleague + Motivator* (n=11)

Unsurprisingly, given the negative discourses around use of AI in education generally, and in higher education specifically, many academics who answered our survey reported feeling guilty or conflicted about their AI use (n=79/1234). Many participants expressed feelings of guilt or shame about using generative AI, even when they find it helpful. For example, one ND participant stated: "there's a guilt att' [sic] - b/c of my different cognition I'm somehow not 'fit for the job'." Another participant notes the "tricky" situation of using AI tools when supervisors and academics see it as "cheating." There was also a sense of anger and disappointment towards the limitations and shortcomings of generative AI. Participants describe some outputs as "garbage", "bullshit", "useless, biased or preachy" and accuse it of producing "underwhelming" or "poor" results. Underlying these emotions is a general distrust and scepticism towards generative AI, with participants expressing concerns about its reliability, accuracy, and ability to truly understand and engage with complex academic work. As one person stated, "I haven't found one that's so useful I use it daily."

The emergence of AI as 'Colleague' and 'Assistant' reflects how metricisation has eliminated many traditional support roles within universities. Neurodivergent academics (and a significant number of non-ND academics) are essentially reconstructing these support networks through AI, managing both the cognitive demands of their discipline and the emotional labour of institutional navigation.

Discussion

This study reveals how academics are using AI as the new 'Invisible workers' (Szekeres, 2004) to navigate what Burrows (2012) terms the 'metricised university' - where academic worth is increasingly measured through quantifiable outputs rather than qualitative contributions. While our study shows that there is little difference in the frequency of use between neurodivergent and non-neurodivergent academics, the headline statistic hides a profound difference in how the technology is being used. Our findings suggest that AI tools are being leveraged not just for cognitive support, but to manage the emotional labour (Hochschild, 1983) demands that metricisation places on all academics, with neurodivergent scholars experiencing these pressures particularly acutely.

The heightened use of AI for writing tasks among neurodivergent academics (+17%, $p < 0.0001$) reflects the particular cognitive demands of academic writing, which simultaneously requires complex executive function skills—organization, planning, sustained attention—and theory of mind abilities to anticipate reader needs and navigate disciplinary conventions (Jurecic, 2007). For many neurodivergent academics, these dual cognitive loads can be overwhelming, making AI a valuable intermediary that can help translate internal thoughts into externally coherent prose or provide feedback on whether their writing successfully communicates to an intended audience. This pattern suggests that AI tools are particularly effective at supporting the intersection of cognitive challenges, offering both structural writing assistance and serving as a proxy reader to help bridge the communication gaps that can arise from differences in social cognition and understanding of implicit academic writing norms. The heightened AI use for writing tasks among neurodivergent academics reflects how academic writing has become increasingly commodified within metricised systems. Each paper, grant application, and report becomes a unit of measurement in academic performance reviews. For neurodivergent academics, the emotional labour of translating their cognitive processes into neurotypical academic discourse while simultaneously meeting productivity metrics creates a compounded burden that AI helps to mediate.

The 'Service Dog' phenomenon reveals how neurodivergent academics must perform additional emotional labour to navigate institutional environments designed around neurotypical norms. This includes managing sensory overload during meetings counted toward 'service' metrics, translating between their cognitive patterns and the linear reporting structures demanded by milestone systems, and maintaining professional personas that mask neurodivergent traits to avoid negative performance evaluations. The significantly higher likelihood of neurodivergent academics to use AI as a 'Service Dog' (+36% compared to non-neurodivergent colleagues) can be understood within the context of the systemic barriers ND colleagues face in academic environments. A recent systematic review of neurodivergent research students (Authors, 2025) revealed pervasive challenges including executive functioning difficulties, navigating opaque academic "hidden curricula," managing sensory and environmental overstimulation, and dealing with inadequate institutional support systems. These challenges mirror precisely the areas where neurodivergent academics in our study described AI as providing "cognitive body doubles," supporting executive function tasks like organization and time management, and offering relief from the social-communicative demands of academic work. Just as the doctoral students in the review struggled with "filing papers," "answering important emails," and managing the cognitive load of multiple tasks, the academics using AI as a Service Dog found tools that could assist with these routine, but cognitively demanding, activities. This pattern suggests that AI tools are filling critical gaps left by institutional failures to adequately support neurodivergent academics, effectively serving as technological accommodations for cognitive and executive function needs that traditional university disability services have historically struggled to address effectively. While AI effectively becomes a mediator for this emotional labour, handling routine communications and administrative tasks that require significant cognitive-emotional translation work for neurodivergent users, we must ask: at what cost?

Limitations

This main limitation of this paper come from the data itself. The binary nature of the adoption question (having used AI or not) does not fully capture the nuance and varying degrees of engagement with these technologies. We did not differentiate between experimental, occasional, or systematic use of AI tools, nor did we explore the specific academic tasks for which respondents employ these technologies. Additionally, the questions do not distinguish between different generative AI platforms, which vary considerably in their capabilities, accessibility, and output quality.

The sample was a non-probability sample which further limits the generalizability of the result to a larger population. Nonetheless the sizeable sample size affords some reassurance of a reasonably representative sample, justifying the inclusion of the p-values for hypothesis tests in Tables 1 and 2.

The survey's timing may also influence responses, as the generative AI landscape is rapidly evolving, with new tools and institutional policies emerging frequently. Furthermore, self-reported utility assessments may be influenced by respondents' prior expectations, technical proficiency, or disciplinary norms regarding technology adoption. The absence of questions addressing ethical considerations, institutional guidance, or specific barriers to adoption limits our understanding of the contextual factors shaping AI use in academic work.

Finally, as these questions represent only a small portion of a broader survey on academic work experiences, they may not have received the same depth of consideration from respondents as the survey's primary focus areas. All these limitations provide obvious starting points for further scholarly examination, using more in-depth qualitative methods. It’s our hope this paper provides some useful starting points for this work.

Conclusion

Our findings expose how metricisation creates particular burdens for neurodivergent academics, who must not only meet quantitative targets but do so while managing the emotional labour of constant self-advocacy and environmental adaptation. The turn to AI tools represents an informal accommodation system where individuals purchase (literally and figuratively) solutions to systemic failures. This raises critical questions about equity: why should neurodivergent academics bear the emotional and financial burden of self-accommodation in increasingly metricised systems?"

There is clearly a ‘support vacuum’ in Higher Education, created by the withdrawal of human support in the form of assistants, librarians, editors. The complex nature of academic work is facing a human drought, which is now being supplied by synthetic colleagues and assistants. This change is not an unalloyed good or bad, but does demand our critical engagement. In this paper we have advanced an argument for AI as a valuable, if informal, assistive technology – and not just for neurodivergent academics. The way AI tools have been taken up by 50% of our participants, and the uses to which they are being put, exposes significant systemic failures within institutional support structures for neurodivergent and neurodivergent alike. As ever, neurodivergent academics face more systemic disadvantage. The fact that neurodivergent academics are turning to commercial AI platforms for basic executive function support—tasks like organizing work, managing deadlines, and processing information— means these individuals must essentially self-accommodate, using whatever tools are available. This creates concerning equity issues: access to effective AI tools often depends on financial resources, technological literacy, and can be hampered by institutional policies about AI use. Furthermore, the current patchwork approach—where individual academics must find and implement their own technological solutions—places the burden of accommodation on those who are already managing systemic barriers. These findings underscore the urgent need for institutions to reconceptualize how academic work could – and should – be supported and what ‘accommodations’ can mean.

AI tools can be legitimate assistive technologies at the same time as being are potential threats to academic integrity. This paradox—where AI simultaneously enables and exposes systemic failures—presents both risk and opportunity. If we can move beyond viewing AI as either saviour or threat, we might instead see it as a catalyst for long-overdue conversations about what truly inclusive academic support looks like in the 21st century.

AI declaration

In the preparation of this manuscript, we made use of OpenAI’s ChatGPT (GPT-4), Claude 3.7 Sonnet from Anthropic, Consensus (https://consensus.app) and Gemini from Google via NotebookLM to assist with various aspects of the writing process. AI was employed primarily for the purposes of idea development, refinement of expression, and assistance with structural editing, particularly to clarify phrasing, improve coherence, and explore alternative formulations of key arguments. We used Claude AI to produce the first draft of the discussion section by using it to analyse our findings in conjunction with findings from a previous paper and producing a synthesis of the two. All conceptual framing, analytical insights, and interpretive claims are our own. We used MaxQDA ‘tailwind’ to interrogate the survey data and Claude 3.7 Sonnet from Anthropic to generate an initial ‘code-book’, before coding the data by hand and producing the analysis.

Ethics approval

This research was approved by [university] ethics committee H/2023/1106

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