INTELLIGENT TECHNOLOGIES IN EDUCATION

The Impact of AI on Academics' and Students' Wellbeing in Higher Education: An Introduction to the Special Issue

Andrew Woon[1], Nurun Nahar[2], Olatunde Amoo Durowoju[3], Mandy Mok[4]
[1]Monash University Malaysia, Malaysia
[2]University of Greater Manchester, United Kingdom
[3]Liverpool John Moores University, United Kingdom
[4]Raffles University, Malaysia

Editorial

Generative artificial intelligence (GenAI) has become increasingly integrated into higher education over the past three academic years. Tools such as ChatGPT, Microsoft Copilot and Google Gemini are now used by students to draft assignments, by academics to prepare teaching materials, and by institutions as they consider the future of assessment. A recent report commissioned by the Higher Education Policy Institute (HEPI), based on 1,054 full-time undergraduate students in the United Kingdom, indicates that GenAI use rose from 66% in 2024 to 95% in 2026, with 94% of respondents using GenAI in connection with assessed work. The same survey reported that around 15% of UK undergraduates use AI for friendship, company, advice or to address loneliness, while 8% use AI alone for counselling or therapy. The uneven distribution of these uses among students suggests that the relationship between AI use and social connection is unlikely to be uniform (Stephenson & Armstrong, 2026). The pace of this change appears to have exceeded the sector's capacity to understand its human consequences. Much of the early literature has tended to prioritise questions of academic integrity, detection and performance (Rudolph et al., 2024; Weber-Wulff et al., 2023), continuing a longer-standing tendency in research on artificial intelligence in higher education to give limited attention to the educators and students who work with these systems (Zawacki-Richter et al., 2019). This special issue reflects a shift towards a central question: how does the presence of GenAI affect the psychological, social and professional wellbeing of people who work and study in universities?

The title uses the broader label AI, following the call for papers, but the discussion that follows focuses mainly on GenAI. Two other applications also feature: AI-text detection software and automated marking. We distinguish these because their wellbeing implications differ in kind. GenAI tools are largely adopted by individuals, who can, to some extent, bound or adapt their own use; the concerns raised therefore centre on reliance, skill and professional identity. Detection software and automated marking, by contrast, are applied to people by institutions, raising concerns about surveillance, trust and fairness. The papers gathered here touch on both, and we seek to keep these categories analytically distinct.

The scope of the issue is deliberately broad, spanning both academic staff and students, because the two groups' experiences of GenAI are closely related. A policy intended to protect academic integrity, such as automated detection, may be experienced directly and sometimes negatively

by students, while students' growing use of GenAI for explanation and reassurance may, in turn, influence the nature of teaching, assessment and mentoring. The topic is also timely: institutions are making significant decisions about AI policy, procurement, detection software and assessment design, some of which may be difficult to reverse, while the evidence base on their wellbeing consequences is still developing. The issue invites the field to treat wellbeing as a central design consideration rather than as a concern addressed only after a technology has been embedded. Its publication in a journal concerned with intelligent technologies in education reflects our view that wellbeing can usefully form part of how such technologies are evaluated. The sections that follow review the literature, describe the call and review process, and then consider the three contributions, the tensions across them and directions for future research.

Background and Context

The call for papers adopted a broad conception of academic wellbeing, encompassing the psychological, emotional and social health of students, faculty and staff within educational settings (Diener et al., 2018; Oades et al., 2011; Stallman, 2010). This framing treats the university as a shared environment in which the experiences of staff and students are interdependent, and it situates GenAI within populations already under pressure: university students report higher levels of psychological distress than the general population (Stallman, 2010), while a systematic review identified high stress, burnout and low wellbeing among university staff (Urbina-Garcia, 2020). The wellbeing consequences of GenAI may therefore be better understood in terms of whether the technology alleviates, redistributes or intensifies existing pressures.

For students, potential benefits include personalised learning that may reduce stress through self-paced progress (Luckin et al., 2016) and conversational agents that extend support beyond the hours during which human services are available. However, a meta-analysis found that agents designed for mental health reduced symptoms of depression and distress without significantly improving overall wellbeing, and its findings may not transfer to the general-purpose assistants most students use (Li et al., 2023). Alongside these benefits are risks of substitution. Excessive reliance on AI has been associated with isolation, anxiety and weakened interpersonal skills (Klimova & Pikhart, 2025); chatbot use among 387 students was linked to some perceived social support but to a negative overall effect on achievement once loneliness and belonging were considered (Crawford et al., 2024); and workload pressure predicted ChatGPT use, which in turn predicted procrastination, self-reported memory loss and lower performance (Abbas et al., 2024). Experiments report performance gains while using the tool followed by lower unaided performance, an effect largely mitigated by pedagogical safeguards (Bastani et al., 2025), or gains that were not matched by improvements in knowledge or transfer (Fan et al., 2025). Much of this evidence comes from school or laboratory settings (see also Kundu & Bej, 2025), so it may be more productive to ask under what conditions GenAI supports, rather than replaces, students' own capabilities and relationships than whether it is beneficial or harmful in general.

The mechanisms that institutions have adopted to protect academic integrity may also carry wellbeing implications. An evaluation of fourteen AI-text detection tools concluded that none was sufficiently accurate or reliable for use in academic settings (Weber-Wulff et al., 2023), and such tools have been shown to misclassify the writing of non-native English speakers as AI-generated disproportionately (Liang et al., 2023), which may raise particular concerns for highly internationalised systems such as those of the United Kingdom and Malaysia. Students have reported

anxiety about being falsely accused of misconduct, and a majority indicated that the way they are assessed has changed considerably in response to AI (Stephenson & Armstrong, 2026). These findings suggest that integrity policy may itself be one of the factors shaping student wellbeing.

For academics, the call identified a comparable mixture of opportunity and risk. GenAI may streamline marking, feedback and administration, potentially reducing workload and burnout (Bobula, 2024; Luckin et al., 2016), but this optimism draws largely on conceptual and advocacy literature rather than on studies measuring workload or wellbeing in universities. Evidence from the wider labour market is mixed: German longitudinal data show no average decline in wellbeing among workers in AI-exposed occupations, although workers' own perceptions of exposure are associated with modest reductions in job and life satisfaction (Giuntella et al., 2025), suggesting that how workers perceive AI may matter alongside its effects on their tasks. Three concerns appear particularly relevant. The first is technostress, which tends to be more pronounced where institutional support is inadequate (Bondanini et al., 2020). In a survey of 1,681 faculty members across 28 countries, 40 per cent described themselves as being at an early stage of AI literacy and 80 per cent reported a lack of clarity about how AI could be applied to teaching (Digital Education Council, 2025). The second is professional identity: as routine teaching is automated, the academic role may shift towards facilitation and mentorship (Holmes et al., 2019), reviving debates about what is distinctively human in teaching (Selwyn, 2019). Academics with lower AI proficiency were also more likely to see AI as a threat to their employment (Digital Education Council, 2025). The third is the ethical and political dimension of AI at work, including data privacy, surveillance, the meaningfulness of work and job displacement (Santoni de Sio, 2024).

These concerns sit within a financially constrained and unevenly regulated context. More than a third of higher education providers in England reported a deficit in 2024–25, and student-to-staff ratios are forecast to rise over the next two years (Office for Students, 2026). GenAI may therefore be adopted partly for reasons of cost, with efficiency gains absorbed as institutional savings rather than returned to staff and students as time for the relational work that supports wellbeing. The European Union's Artificial Intelligence Act designates several educational applications as high-risk and prohibits emotion recognition in educational institutions, in part because of the power imbalance between institutions and learners (European Union, 2024), whereas other jurisdictions rely more heavily on non-binding guidance, such as UNESCO's human-centred approach (Miao & Holmes, 2023). Practice within institutions also varies: UK undergraduates are divided almost equally on whether their institution encourages the use of AI, and patterns of use differ by socio-economic background, gender and discipline (Stephenson & Armstrong, 2026). Access to tools, the data protections associated with them and the training that accompanies them are therefore likely to influence who benefits from GenAI and who bears its risks.

Taken together, the literature points to gains in efficiency and access, documented integrity and epistemic risks, and technostress where institutional support is weak. What remains less clear is how these threads interact once the individual, rather than institutional policy, is placed at the centre. Does the efficiency gain outweigh the psychological cost of surveillance and detection anxiety, or does it displace that cost from one part of the academic experience to another? Is deskilling a measurable phenomenon, or a concern that currently exceeds the available evidence? And to what extent do the difficulties reported by staff and students arise from GenAI itself rather than from ambiguity in the institutional responses surrounding it? Research also rarely treats flourishing, professional identity and psychological need satisfaction as primary outcomes. The frameworks most commonly applied to educational technology, including the Technology Acceptance Model

and the Unified Theory of Acceptance and Use of Technology (Davis, 1989; Venkatesh et al., 2003), mainly explain adoption and say less about the consequences of sustained use. Studies that examine staff and students together, attend to relational processes such as belonging and mentorship, or compare national contexts also appear to be less common. The issue was framed around this gap.

Overview of the Call and Process

The special issue was announced through an open call for papers on the theme of "The Impact of Artificial Intelligence (AI) on Academics and Student Wellbeing in Higher Education," inviting contributions on faculty workload and identity, student mental health and engagement, social connection and belonging, and the policy frameworks that shape all three. Prospective authors first submitted a blinded abstract of up to 250 words, which the guest editorial team screened for fit with the issue's scope and theoretical grounding before inviting full manuscripts. Full submissions then passed through the journal's standard double-anonymous peer review process within the "AI in Higher Education: Academic and Wellbeing Impacts" section, coordinated by the guest editors alongside the journal's editorial team. The three papers gathered here were selected from that process because, taken together, they offer complementary methodological approaches (friendship-based conversation, semi-structured interviews and an open-ended survey) and complementary theoretical lenses (flourishing theory, self-determination theory and self-identity theory) on a shared underlying question.

Synthesis of Contributions

Rather than treating the three papers as independent case studies, it is more useful to read them as two conversations organised around a shared boundary: the line between AI as an augmentative presence in academic life and AI as a substitute for human judgement and relationships. The first conversation is anchored in the student experience of that boundary; the second is anchored in the academic experience. Read in this way, the papers do not simply sit side by side; they answer one another.

Flourishing and the augmentation boundary: the student experience

Beckingham, Gray, Mellon and Parkin address the problem of how GenAI shapes student flourishing once the analytic lens is widened beyond academic performance to encompass the full range of students' personal, academic and emerging professional lives. Their approach draws on the Listening Room methodology (Heron, 2020), in which friendship trios talk to one another with minimal researcher intervention, and structures the resulting data around the eight components of the Flourishing Scale developed by Diener et al. (2010). The paper's key contribution is to show, empirically, that students themselves negotiate the augmentation/substitution boundary with considerable sophistication. While they value AI as a tool for supporting understanding, task management and communication, they simultaneously articulate clear concerns about academic integrity, fairness, over-reliance, skill atrophy and authenticity. This indicates that students do not view GenAI as an unproblematic replacement for their own effort or judgement; rather, they actively distinguish between acceptable forms of assistance that enhance learning and uses that may undermine personal development, assessment validity or ethical academic practice. This connection to the issue's theme is direct: it operationalises "flourishing" as a set of concrete, contestable

everyday judgements that students make about where GenAI belongs, rather than as an abstract wellbeing score.

Blommerde, Gibbins, Richards, Hall and Veuger take up a closely related problem from a joint staff-and-student vantage point, asking how efficiency gains from GenAI interact with the psychological needs identified by Self-Determination Theory: autonomy, competence and relatedness (Ryan & Deci, 2020). Their Students as Partners study, based on semi-structured interviews with fifteen staff and students, yields a conceptually significant contribution to the issue: the Efficiency-Erosion Paradox. According to participants' accounts, the same features that make GenAI efficient may also erode the psychological conditions for flourishing rather than merely trading one benefit against another. As a proposition grounded in fifteen interviews, it is better read as a hypothesis to be tested than as a demonstrated effect (see Section 6). For students specifically, the finding that detection software produces a "weird limbo period" of algorithmic suspicion suggests how Beckingham et al.'s augmentation boundary may be experienced when institutions, rather than students, misjudge where that boundary lies.

Identity under renegotiation: the academic experience

Blommerde et al.'s staff-facing findings also open the second conversation. Their participants frame automated marking as a "line in the sand" for professional identity, arguing that an algorithm cannot hold the longitudinal, relational knowledge accumulated over three years that a marker needs to assess a student fairly. Enang and Christopoulou take this problem of identity threat as their central concern, surveying 43 academics at a UK management school and analysing their accounts through self-identity theory (Burke & Stets, 2009). Unlike the other two papers, which employed facilitated discussions, this study used an open-ended, anonymous survey spanning academic ranks, a format the authors chose because it was more likely to elicit candid responses on sensitive topics. This may help explain the frankness of some accounts, including concerns about the relevance of academic roles should ChatGPT become capable of producing new knowledge. The paper's key contribution is to show that identity threat and identity opportunity are not neatly separated but can coexist within a single participant's account. The authors describe participants who used ChatGPT, questioned its legitimacy, defended established academic values and imagined new roles, sometimes all at once. One respondent, for example, anticipated academics producing knowledge that feeds ChatGPT, which in turn teaches students, while also reflecting, "We may end up demonstrating to students how to appropriately use ChatGPT." Because the responses are analysed thematically, the paper does not reveal how often both reactions occur in the same person. Its connection to the issue's theme is to relocate the augmentation/substitution boundary from a question about student behaviour to a question about what remains distinctively human in academic expertise itself—the same boundary that Beckingham et al. and Blommerde et al. examine from the other side of the lectern.

Cross-Cutting Themes and Tensions

Reading the three papers reveals a set of wellbeing-related patterns across the three distinct datasets.

A first and recurring pattern is the prominence of relatedness as a key psychological need underpinning participants' experiences, whether conceptualised through Diener's model, Ryan and Deci's framework, or the relational foundations of self-identity theory. Participants across all three studies tolerate a great deal of AI involvement in the mechanics of academic work, provided that the human relationship at its centre (mentor and mentee, marker and student, colleague and colleague) remains visibly intact. A second pattern is a shared, if variously named, concern about a mastery or

competence gap: the fear that GenAI's capacity to satisfy the immediate feeling of competence may substitute for, rather than build, durable and transferable skills. A third pattern is that policy ambiguity emerges as an important source of concern alongside GenAI itself: participants' accounts point to unclear declaration rules, inconsistent journal disclosure norms and detection software of acknowledged unreliability. Because the studies do not set out to separate the effects of GenAI from those of its institutional context, we cannot say how much of the reported wellbeing cost is attributable to each.

This leaves an open question about remedies: whether the answer lies in better AI governance, better technology (for example, more reliable detection), or a more fundamental rethinking of assessment that reduces reliance on detection altogether. Read together, the papers converge more than they diverge: all three look to institutions and governance rather than to technical fixes, and none presents more reliable detection as its main answer. They differ in emphasis. Enang and Christopoulou's participants call chiefly for operational clarity, and the authors recommend institution-wide rules on acceptable use and disclosure, consistent journal policies, and staff development that includes AI-informed assessment design. Blommerde et al. address detection and marking most directly, reporting that automated detection creates technostress and erodes trust, and that staff and students reject machine-led marking; in response, they propose a co-created form of "Relational Governance". Beckingham et al. likewise call for human-centred institutional guidance that gives wellbeing a place alongside integrity and academic outcomes. Governance is therefore the common thread; assessment redesign is most explicit in Enang and Christopoulou, while the case against detection is made most strongly by Blommerde et al. The evidence in this issue is better suited to showing what participants find harmful than to adjudicating between remedies.

A methodological pattern is also worth identifying as a limitation of the collection as a whole: all three studies are qualitative, UK-based and drawn from a single institution each. This yields depth and recurring themes across independent samples but leaves open how far these dynamics generalise across national systems, institution types or disciplines with different assessment cultures.

Future Directions

The issue points towards several concrete openings for future work. Longitudinal designs are needed to test whether the mastery gap identified across all three papers is a transient adjustment cost or a durable feature of GenAI-saturated learning, ideally tracked across a full degree cycle rather than a single module or semester. Cross-institutional and cross-national replication would help establish whether the relational boundaries identified here hold across disciplines with different norms of assessment and mentorship, and outside the UK context. For example, it remains unclear whether findings such as the rejection of AI-automated marking reported by Blommerde et al. would be observed in other educational and national settings. There is also a clear opening for quantitative work that operationalises and tests the mechanisms proposed inductively here, such as the Digital Surveillance Paradox and the Efficiency-Erosion Paradox, against validated wellbeing and motivation measures at scale. Finally, Beckingham et al. gesture towards, but do not fully examine, the more intimate and personal uses of GenAI: as an emotional confidant, a proxy for mentorship, or a coping tool for anxiety. Participants alluded to these uses but were reluctant to discuss them in full. Given the seriousness with which participants in this issue treated them, even in passing, this remains, in our view, the most under-examined and urgent frontier for wellbeing research in this area.

Closing

We are grateful to the authors of the three papers gathered here for the care with which they listened to their participants, and to the peer reviewers whose close and constructive engagement with these manuscripts strengthened each contribution and helped situate it within the wider field. We also thank the participants themselves, including students and academic staff across three UK institutions, for their candour in discussing a topic that touches on genuine anxieties about integrity, competence and professional worth.

It is our hope that this issue does more than document a moment of technological disruption. Participants' accounts suggest that GenAI supports flourishing in specific, identifiable ways and may undermine it in others; they also suggest that the human and institutional relationships within which the technology is embedded matter at least as much as the technology itself. Two implications follow for institutions and for those who evaluate technology on their behalf. First, because the papers repeatedly identify ambiguity in institutional guidance as a source of concern, clear and operational guidance on acceptable use and disclosure—co-created, as Blommerde et al. propose—is better treated as a wellbeing measure than as an administrative one. Second, because detection software and automated marking are applied to people rather than used by them, institutions should weigh their effects on trust and relatedness before adopting them, and should treat wellbeing as a criterion in procurement and assessment decisions rather than as a matter for review afterwards. We hope the issue offers the field, and the institutions it serves, a more precise and more human vocabulary for that ongoing negotiation.

References

Abbas, M., Jam, F. A., & Khan, T. I. (2024). Is it harmful or helpful? examining the causes and consequences of generative AI usage among university students. *International Journal of Educational Technology in Higher Education*, *21*, 10. https://doi.org/10.1186/s41239-024-00444-7

Bastani, H., Bastani, O., Sungu, A., Ge, H., Kabakcı, Ö., & Mariman, R. (2025). Generative AI without guardrails can harm learning: Evidence from high school mathematics. *Proceedings of the National Academy of Sciences*, *122*(26), e2422633122. https://doi.org/10.1073/pnas.2422633122

Beckingham, S., Gray, J., Mellon, V., & Parkin, H. J. (2026). Techno-wellbeing and flourishing in higher education: Student experiences of using generative AI. *Intelligent Technologies in Education*. https://doi.org/10.53761/zycb3c32

Blommerde, T., Gibbins, K., Richards, H., Hall, J., & Veuger, S. (2026). Between efficiency and erosion: The impact of generative AI on academic professional identity and student flourishing in higher education. *Intelligent Technologies in Education*. https://doi.org/10.53761/ksqxex16

Bobula, M. (2024). Generative artificial intelligence (AI) in higher education: A comprehensive review of challenges, opportunities, and implications. *Journal of Learning Development in Higher Education*, (30). https://doi.org/10.47408/jldhe.vi30.1137

Bondanini, G., Giorgi, G., Ariza-Montes, A., Vega-Muñoz, A., & Andreucci-Annunziata, P. (2020). Technostress dark side of technology in the workplace: A scientometric analysis. *International Journal of Environmental Research and Public Health*, *17*(21), 8013. https://doi.org/10.3390/ijerph17218013

Burke, P. J., & Stets, J. E. (2009). *Identity theory*. Oxford University Press.

Crawford, J., Allen, K.-A., Pani, B., & Cowling, M. (2024). When artificial intelligence substitutes humans in higher education: The cost of loneliness, student success, and retention. *Studies in Higher Education*, *49*(5), 883–897. https://doi.org/10.1080/03075079.2024.2326956

Davis, F. D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. *MIS Quarterly*, *13*(3), 319–340. https://doi.org/10.2307/249008

Diener, E., Oishi, S., & Tay, L. (2018). Advances in subjective well-being research. *Nature Human Behaviour*, *2*(4), 253–260. https://doi.org/10.1038/s41562-018-0307-6

Diener, E., Wirtz, D., Tov, W., Kim-Prieto, C., Choi, D., Oishi, S., & Biswas-Diener, R. (2010). New well-being measures: Short scales to assess flourishing and positive and negative feelings. *Social Indicators Research*, *97*(2), 143–156. https://doi.org/10.1007/s11205-009-9493-y

Digital Education Council. (2025). *What faculty want: Key results from the global AI faculty survey 2025*. https://www.digitaleducationcouncil.com/dec-insights/what-faculty-want-key-results-from-the-global-ai-faculty-survey-2025

Enang, E., & Christopoulou, D. (2026). Between promise and peril: Educators' perspectives on ChatGPT and its impact on professional identity. *Intelligent Technologies in Education*. https://doi.org/10.53761/d7vte220

European Union. (2024). Regulation (EU) 2024/1689 of the european parliament and of the council of 13 june 2024 laying down harmonised rules on artificial intelligence (artificial intelligence act). https://eur-lex.europa.eu/eli/reg/2024/1689/oj

Fan, Y., Tang, L., Le, H., Shen, K., Tan, S., Zhao, Y., Shen, Y., Li, X., & Gašević, D. (2025). Beware of metacognitive laziness: Effects of generative artificial intelligence on learning motivation, processes, and performance. *British Journal of Educational Technology*, *56*(2), 489–530. https://doi.org/10.1111/bjet.13544

Giuntella, O., König, J., & Stella, L. (2025). Artificial intelligence and the wellbeing of workers. *Scientific Reports*, *15*. https://doi.org/10.1038/s41598-025-98241-3

Heron, E. (2020). Friendship as method: Reflections on a new approach to understanding student experiences in higher education. *Journal of Further and Higher Education*, *44*(10), 1383–1395. https://doi.org/10.1080/0309877X.2018.1541977

Holmes, W., Bialik, M., & Fadel, C. (2019). *Artificial intelligence in education: Promises and implications for teaching and learning*. Center for Curriculum Redesign.

Klimova, B., & Pikhart, M. (2025). Exploring the effects of artificial intelligence on student and academic well-being in higher education: A mini-review. *Frontiers in Psychology*, *16*, 1498132. https://doi.org/10.3389/fpsyg.2025.1498132

Kundu, A., & Bej, T. (2025). Psychological impacts of AI use on school students: A systematic scoping review of the empirical literature. *Research and Practice in Technology Enhanced Learning*, *20*, 030. https://doi.org/10.58459/rptel.2025.20030

Li, H., Zhang, R., Lee, Y.-C., Kraut, R. E., & Mohr, D. C. (2023). Systematic review and meta-analysis of AI-based conversational agents for promoting mental health and well-being. *npj Digital Medicine*, *6*, 236. https://doi.org/10.1038/s41746-023-00979-5

Liang, W., Yuksekgonul, M., Mao, Y., Wu, E., & Zou, J. (2023). GPT detectors are biased against non-native english writers. *Patterns*, *4*(7), 100779. https://doi.org/10.1016/j.patter.2023.100779

Luckin, R., Holmes, W., Griffiths, M., & Forcier, L. B. (2016). *Intelligence unleashed: An argument for AI in education*. Pearson. https://discovery.ucl.ac.uk/1475756/

Miao, F., & Holmes, W. (2023). *Guidance for generative AI in education and research*. UNESCO. https://unesdoc.unesco.org/ark:/48223/pf0000386693

Oades, L. G., Robinson, P., Green, S., & Spence, G. B. (2011). Towards a positive university. *The Journal of Positive Psychology*, *6*(6), 432–439. https://doi.org/10.1080/17439760.2011.634828

Office for Students. (2026). *Financial sustainability of higher education providers in england 2026* (OfS 2026.21). Office for Students. Bristol. https://www.officeforstudents.org.uk/media/p0dd3sdq/ofs-2026_21-updated-15-6-26.pdf

Rudolph, J., Ismail, M. F. B. M., & Popenici, S. (2024). Higher education's generative artificial intelligence paradox: The meaning of chatbot mania. *Journal of University Teaching and Learning Practice*, *21*(6). https://doi.org/10.53761/54fs5e77

Ryan, R. M., & Deci, E. L. (2020). Intrinsic and extrinsic motivation from a self-determination theory perspective: Definitions, theory, practices, and future directions. *Contemporary Educational Psychology*, *61*, 101860. https://doi.org/10.1016/j.cedpsych.2020.101860

Santoni de Sio, F. (2024). Artificial intelligence and the future of work: Mapping the ethical issues. *The Journal of Ethics*, *28*, 407–427. https://doi.org/10.1007/s10892-024-09493-6

Selwyn, N. (2019). *Should robots replace teachers? AI and the future of education*. Polity Press.

Stallman, H. M. (2010). Psychological distress in university students: A comparison with general population data. *Australian Psychologist*, *45*(4), 249–257. https://doi.org/10.1080/00050067.2010.482109

Stephenson, R., & Armstrong, C. (2026). *Student generative AI survey 2026* (HEPI Report 199). Higher Education Policy Institute. Oxford. https://www.hepi.ac.uk/reports/student-generative-ai-survey-2026/

Urbina-Garcia, A. (2020). What do we know about university academics' mental health? a systematic literature review. *Stress and Health*, *36*(5), 563–585. https://doi.org/10.1002/smi.2956

Venkatesh, V., Morris, M. G., Davis, G. B., & Davis, F. D. (2003). User acceptance of information technology: Toward a unified view. *MIS Quarterly*, *27*(3), 425–478. https://doi.org/10.2307/30036540

Weber-Wulff, D., Anohina-Naumeca, A., Bjelobaba, S., Foltýnek, T., Guerrero-Dib, J., Popoola, O., Šigut, P., & Waddington, L. (2023). Testing of detection tools for AI-generated text. *International Journal for Educational Integrity*, *19*, 26. https://doi.org/10.1007/s40979-023-00146-z

Zawacki-Richter, O., Marín, V. I., Bond, M., & Gouverneur, F. (2019). Systematic review of research on artificial intelligence applications in higher education – where are the educators? *International Journal of Educational Technology in Higher Education*, *16*, 39. https://doi.org/10.1186/s41239-019-0171-0