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Generative AI and Academic Employee Well-Being: An Integrative HRM Review of Job Crafting and Technostress Pathways

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ABSTRACT

Generative artificial intelligence (GenAI) is reshaping academic work, yet its implications for academic employee well-being remain fragmented across higher education, human resource management (HRM), occupational health, and information systems research. This structured integrative review synthesises two contrasting pathways: job crafting, through which employees convert GenAI affordances into job resources, and technostress, through which new demands can erode well-being. Three Scopus searches identified 444 records; 12 duplicates were removed, 432 records were screened, and 18 complete reports representing 17 independent evidence clusters were included. The evidence indicates that GenAI may provide cognitive assistance, task redesign, autonomy, and engagement, but may also generate verification workload, techno-complexity, uncertainty, anxiety, and work intensification. The direct academic evidence is strongest for technostress, workload, anxiety, and well-being; evidence for GenAI-enabled job crafting among lecturers remains emergent and is supported partly by transferable workplace studies.. The review contributes an HRM-oriented dual-pathway framework for sustainable GenAI-enabled academic work without claiming causal mediation

Keywords: Academic Employee Well-Being; Generative Artificial Intelligence; Human Resource Management; Job Crafting; Job Demands–Resources Theory; Technostress.

INTRODUCTION

Generative artificial intelligence (GenAI) is moving from experimental use to an ordinary component of academic work. Lecturers use it to generate teaching ideas, structure learning materials, translate and edit text, develop preliminary analyses, prepare administrative communication, and explore research questions. These applications can shorten selected tasks and widen access to cognitive assistance. Yet the occupational value of that assistance is not self-evident. Faculty studies report marked differences in readiness, confidence, perceived usefulness, anxiety, and well-being, indicating that adoption rates or output speed cannot establish whether GenAI improves the quality of academic working life (Bolívar-Cruz & Verano-Tacoronte, 2025; Cambra-Fierro et al., 2025; Liu et al., 2025; Verano-Tacoronte et al., 2025).

The central problem is a redistribution rather than a simple removal of effort. Drafting may become faster, while responsibility for fact checking, source verification, privacy, authorship, academic integrity, and pedagogical judgement remains with the lecturer. Efficiency can therefore release time, but it can also move work into less visible monitoring and correction activities. This distinction matters because universities may convert perceived efficiency into higher performance expectations before recognising the additional verification labour required to use probabilistic systems responsibly. Under those conditions, the same tool can function as a job resource and a new job demand within a single task episode.

Existing knowledge remains fragmented across higher education, organisational behaviour, information systems, occupational health, and HRM. Academic studies predominantly examine readiness, instructional practice, dependency, anxiety, workload, or well-being. Workplace studies more directly examine AI-enabled job crafting, engagement, technostress, insecurity, and performance. These streams rarely speak to one another. As a result, the literature does not yet adequately explain how lecturers actively redesign AI-enabled work, why an apparently useful system can simultaneously increase strain, or which organisational conditions determine whether benefits are sustainable.

This gap is significant for HRM because lecturers are academic employees and strategic human capital, not merely users of educational technology. Their capacity to teach, research, serve communities, and perform administrative roles depends on sustainable work design. Decisions about AI literacy, autonomy, workload allocation, performance management, leadership support, psychosocial risk, and responsible-use rules therefore belong within an integrated HRM agenda. Treating GenAI only as an innovation-adoption issue can obscure how implementation changes job boundaries, responsibility, and employee well-being.

Accordingly, this structured integrative review asks: (1) how GenAI reshapes academic job demands and resources; (2) how AI-enabled job crafting may support academic employee well-being; (3) how technostress may undermine it; and (4) which HRM and organisational conditions shape the relative strength of these pathways. The review is novel in connecting job crafting and technostress within one Job Demands–Resources (JD–R) explanation, distinguishing direct academic evidence from transferable workplace evidence, and translating the synthesis into an HRM-oriented framework. Its contribution is not a claim of tested mediation; it is an evidence-informed account of why GenAI can empower and intensify academic work at the same time.

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JD–R theory and GenAI-enabled work

JD–R theory explains employee well-being through the balance and interaction between job demands and job resources. Demands require sustained physical, cognitive, or emotional effort and may generate psychological costs when they are intense or poorly supported. Resources help employees attain work goals, reduce the costs of demands, and stimulate learning, motivation, and engagement (Bakker & Demerouti, 2017). The theory is particularly suitable for GenAI because the technology has no fixed occupational meaning. Its effect depends on how technical affordances are incorporated into tasks, evaluated by employees, and governed by the organisation.

In academic work, cognitive assistance, faster drafting, information access, and support for routine communication can operate as resources. However, output opacity, verification requirements, changing institutional rules, reputational accountability, insecurity, and pressure for continuous adaptation can operate as demands. Resources and demands may also be sequential: time saved in producing a draft may be consumed by checking evidence and correcting fabricated or contextually unsuitable content. The relevant analytical unit is therefore not access to GenAI alone, but the configuration of tool, task, employee capability, performance expectation, and organisational support.

Job crafting as the motivational pathway

Job crafting refers to self-initiated changes in task, relational, and cognitive boundaries through which employees make work more workable or meaningful (Tims et al., 2012). In GenAI-enabled academic work, task crafting can involve reallocating routine drafting to the tool while reserving interpretation and judgement for the lecturer. Cognitive crafting can involve redefining professional value around critical evaluation rather than first-draft production. Relational crafting may include peer verification, prompt sharing, or interdisciplinary collaboration. These responses differ from passive adoption because the employee actively reorganises how work is performed.

The reviewed workplace evidence distinguishes approach-oriented crafting from avoidance-oriented responses. Approach crafting seeks additional resources, learning, and meaningful redesign; avoidance responses can involve withdrawal, reduced engagement, or alienation when employees perceive AI as uncontrollable or identity threatening (Dong et al., 2026; Liu et al., 2026). Thus, automation is not automatically beneficial crafting. Benefits are more plausible when employees retain discretion, understand the task, and can evaluate output quality. For lecturers, selective non-use may also be a legitimate protective form of boundary management when tasks contain confidential data, high-stakes assessment, or irreplaceable professional judgement.

Technostress as the health-impairment pathway

Technostress describes strain associated with demands created or intensified by technology. GenAI can create techno-overload when output volume or expected responsiveness increases, techno-complexity when employees must learn unstable systems, techno-uncertainty when tools and policies change rapidly, and techno-insecurity when employees fear skill obsolescence or role displacement. It may also create an accountability asymmetry: generation is delegated to a system, but responsibility for accuracy, fairness, confidentiality, and integrity remains human.

Educator evidence connects these conditions with anxiety, dependency, stress, frustration, and concerns about skill erosion (Alhur et al., 2025; Delello et al., 2025). These reactions do not imply that all technology-related pressure is harmful. A manageable challenge can stimulate learning when employees possess resources and

recovery opportunities. The risk arises when demands accumulate without control, support, clear rules, or recognition of invisible verification work. Technostress is consequently treated as a conditional health-impairment mechanism rather than an unavoidable outcome of using GenAI.

Academic employee well-being and HRM

Academic employee well-being is defined as sustainable positive functioning, manageable strain, and the capacity to perform teaching, research, service, and administrative responsibilities without persistent depletion. It is related to, but analytically distinct from, engagement, job satisfaction, burnout, and general mental health. A narrow focus on short-term productivity may therefore misclassify intensified work as successful adoption even when it weakens recovery, autonomy, or professional confidence.

HRM connects the individual pathways to organisational choices. Development practices shape AI literacy and critical verification capability; work design determines autonomy and task boundaries; performance management influences whether efficiency gains become escalating targets; leadership affects psychological safety and access to support; and governance clarifies acceptable use, disclosure, data protection, and accountability. Figure 2 presents the resulting conceptual framework: GenAI affordances can be converted into resources through job crafting or into demands through technostress, while HRM conditions influence both routes. The framework expresses propositions for later empirical testing rather than hypotheses tested in this review.

RESEARCH METHOD

Review design and search

A structured integrative review was selected because the question spans heterogeneous quantitative, qualitative, review, and conceptual evidence. This design permits theoretical integration across partially separate research traditions while retaining transparent identification, eligibility, appraisal, extraction, and synthesis procedures (Whittemore & Knafl, 2005). Three Scopus search streams examined: (A) GenAI, academic employees, and well-being or strain; (B) AI-enabled job crafting; and (C) AI-related technostress. Searches covered January 2022 to 31 July 2026, English-language final-stage journal articles or reviews, and relevant social-science, management, psychology, economics, and decision-science fields. Older sources were retained only when necessary to define foundational theory or review method.

The search strings were: A—("generative AI" OR "generative artificial intelligence" OR ChatGPT) AND (faculty OR lecturer* OR academic* OR "university teacher*" OR "higher education teacher*" OR educator*) AND ("well-being" OR wellbeing OR stress OR technostress OR anxiety OR burnout OR workload OR "work engagement"); B—("generative AI" OR "generative artificial intelligence" OR ChatGPT OR "artificial intelligence") AND ("job crafting" OR "work crafting" OR "AI crafting"); and C—("generative AI" OR "generative artificial intelligence" OR ChatGPT OR "artificial intelligence") AND (technostress OR "technology stress" OR "technological stress" OR "AI anxiety" OR "digital stress"). Scopus was the completed database source; no claim is made that the search exhausted all multidisciplinary databases.

Eligibility, screening, and retrieval

Table 1. Eligibility criteria

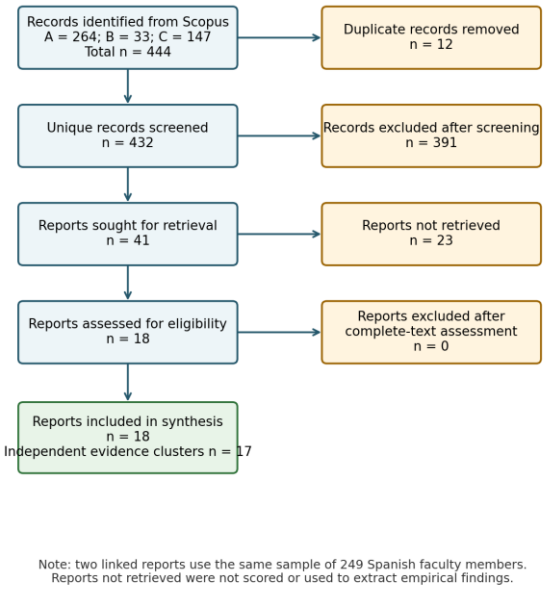
Criterion	Include	Exclude
Publication	Peer-reviewed, final-stage journal article or review	Editorial, news, commentary, book review

Criterion	Include	Exclude
Language/period	English; 2022–31 July 2026	Other language; outside period, except foundational theory/method
Context	Academic employees or transferable professional-work mechanisms	Student-only or non-occupational evidence
Phenomenon	GenAI or clearly specified AI-enabled work practice	Generic digitalisation without identifiable AI
Outcome	Resources/demands, crafting, technostress, work design, occupational well-being	Adoption only, without work-design or well-being relevance
Evidence access	Complete text with sufficient empirical/conceptual detail	Metadata or abstract only

Source: Processed Data (2026)

The three exports contained 444 records (A = 264; B = 33; C = 147). DOI-first, EID-second, and normalised-title matching removed 12 duplicates. An initial screening retained 48 candidates. A subsequent metadata eligibility check reclassified seven of them—five for population or context and two for study direction or year—before retrieval; these seven are therefore counted with screening exclusions rather than as complete-text exclusions. In total, 391 of 432 unique records were excluded before retrieval and 41 reports were sought. Twenty-three were not retrieved. All 18 complete reports assessed for eligibility were included. Two linked Spanish reports used the same 249-person faculty sample, yielding 17 independent evidence clusters. Reports not retrieved were neither scored nor used to extract findings.

Figure 1. Literature identification and selection flow



Source: Authors' Scopus screening and full-text audit (2026).

Quality appraisal

Quality appraisal was conducted only after complete-text eligibility had been established. Because the corpus combined heterogeneous empirical, review, and conceptual designs, a single numerical scale would have created false equivalence. A design-sensitive checklist was therefore used. Empirical studies were judged on alignment between question and design, sampling or case justification, measurement or source transparency, analytical rigour, evidential support, limitations, and relevance. Reviews and conceptual studies were judged on problem clarity, coverage, construct definition, logical coherence, evidential grounding, and generative value. Each criterion was recorded as met, partly met, not met, or not applicable, with a written justification.

The appraisal produced three high-quality, ten moderate-to-high-quality, and five moderate-quality reports. No report was excluded solely because of its rating. Instead, quality and design informed evidential weight during synthesis: convergent findings from stronger direct academic studies received greater interpretive weight than isolated or transferable workplace findings. The complete study-level decisions and limitations are documented in Supplementary Material 1, allowing the judgement process to be audited without overloading the main article.

Data extraction and synthesis

A structured extraction register recorded setting, population, design, sample, AI application, constructs, theoretical lens, measures or evidence base, findings, boundary conditions, limitations, quality judgement, and pathway relevance. First-cycle coding identified affordances, resources, demands, crafting responses, technostress creators, well-being outcomes, and contextual conditions. Second-cycle synthesis compared convergence, contradiction, explanatory mechanisms, and rival interpretations. Linked publications from the same sample were treated as one evidence cluster, preventing double counting.

The synthesis deliberately separated direct academic evidence from workplace bridge evidence. Direct evidence was used to describe lecturer experience and outcomes; bridge studies were used only to clarify mechanisms that might transfer to academic employment. A proposed pathway was retained when it was conceptually coherent and supported by more than a single isolated observation, but the wording was calibrated to design strength. Cross-sectional associations were not restated as causal effects, qualitative accounts were not treated as prevalence estimates, and conceptual relationships were not presented as tested mediation.

RESULTS

Table 2. Characteristics of the 18 included reports

Study	Context	Design	Sample/evidence	Role
Dong et al. (2026)	Knowledge workers, China	Mixed methods: two-wave cross-level survey/HLM	52 teams in survey; 160 knowledge workers in experiment	Bridge: job crafting

Study	Context	Design	Sample/evidence	Role
		plus 2×2 experiment		
Zaim et al. (2026)	University English lecturers, Indonesia	Mixed-method cross-sectional survey, clustering, reflections and interviews	191 lecturers	Academic
Liu, Lei, and Qu (2026)	Employee–leader dyads, China	Scale development plus multi-source, multi-wave survey	287 employee–leader dyads; separate scale-development samples	Bridge: job crafting
Gusti et al. (2026)	Frontline hotel workers, West Sumatra, Indonesia	Cross-sectional survey; PLS-SEM serial mediation	310 workers	Bridge: technostress/well-being
Su, Beh, and Cheah (2026)	Faculty workload in higher education	Systematic review using PRISMA and MMAT	30 empirical studies	Academic
Mu et al. (2026)	Full-time employees with AI experience	Two-wave online survey	252 employees	Bridge: job crafting
Zhang, Awang, and Ahmad (2026)	Faculty at five universities in Shanxi, China	Explanatory sequential mixed methods; PLS-SEM and interviews	384 survey respondents; 10 interviewees	Academic
Li et al. (2026)	Project professionals	Two-wave survey with attention checks	450 valid respondents at Wave 2	Bridge: job crafting
Vuong (2026)	Employees of Vietnamese SMEs	Survey with mediation and moderation analysis	758 employees	Bridge: job crafting
Jin, Yang, and Zhang (2026)	Employees and supervisors in	Two-wave, multi-source	326 matched employee–supervisor pairs	Bridge: technostress/well-being

Study	Context	Design	Sample/evidence	Role
	AI-enabled organisations	survey; PLS-SEM		
Delello et al. (2025)	Educators across multiple countries and educational settings	Cross-sectional online mixed-method survey	334 educators	Adjacent educator
Verano-Tacoronte, Bolívar-Cruz, and Sosa-Cabrera (2025)	Faculty at Spanish public universities	Cross-sectional survey; PLS-SEM	249 faculty members	Academic
Liu et al. (2025)	Business and management faculty, Chinese universities	Cross-sectional survey; CB-SEM and fsQCA	711 faculty members	Academic
Cambra-Fierro et al. (2025)	University faculty, Spain	Cross-sectional survey; CB-SEM	401 professors	Academic
Bolívar-Cruz and Verano-Tacoronte (2025)	Faculty at Spanish public universities	Cross-sectional survey with gender-stratified analysis	249 faculty members	Academic
Alhur et al. (2025)	Medical educators, Palestine	Qualitative interviews and focus groups; thematic analysis	46 educators (22 interviews; 24 focus-group participants)	Academic
Shen and Guo (2024)	Chinese EFL teachers using AI in L2 classes	Qualitative interview study; thematic analysis	50 teachers	Adjacent educator
Shekhar and Saurombe (2026)	Digital workplace discourse	Mixed computational and qualitative analysis	1,454 public workplace narratives	Bridge: technostress/well-being

Source: Processed Data (2026)

Resource conversion and AI-enabled job crafting

The resource pathway begins with cognitive assistance, rapid information processing, task structuring, and relief from selected routine activities. Direct faculty studies associated useful and manageable GenAI adoption with greater happiness, energy, professionalism, or lower stress, although most were cross-sectional and could not establish temporal direction (Cambra-Fierro et al., 2025; Liu et al., 2025; Zhang et al., 2026). The pattern is therefore conditional rather than uniformly positive: assistance became valuable when lecturers could judge output quality and integrate it with existing professional knowledge.

Workplace studies clarified the conversion mechanism. AI embeddedness, growth-oriented appraisal, mindfulness, digital competence, and perceived challenge supported approach-oriented crafting, engagement, performance, or career sustainability (Dong et al., 2026; Li et al., 2026; Mu et al., 2026; Vuong, 2026). Employees did not benefit merely because AI was available; they benefited when they reorganised tasks and retained a sense of agency. Conversely, avoidance crafting could operate through alienation and impair career outcomes (Liu et al., 2026).

For academic employees, the most defensible inference is that GenAI creates crafting opportunities rather than guaranteed crafting outcomes. Lecturers may redirect time from routine production to student interaction, interpretation, or creative inquiry, but the reviewed academic studies rarely measured those changes with established crafting scales. The pathway is consequently supported by direct evidence of resource gain and by transferable evidence of the crafting mechanism. It should be tested among lecturers before being described as causal mediation.

Demand displacement, technostress, and well-being

Efficiency did not consistently reduce total workload. Time saved during generation was often displaced into fact checking, source verification, privacy protection, ethical judgement, integrity monitoring, and adaptation to changing rules (Delello et al., 2025; Su et al., 2026; Zaim et al., 2026). This demand displacement helps explain why lecturers can report usefulness and strain simultaneously. Positive emotion may accompany faster task completion, while anxiety persists because the employee remains accountable for unreliable or inappropriate output.

Educators also described dependency, possible skill erosion, stress, frustration, and uncertainty alongside enjoyment and confidence (Alhur et al., 2025; Shen & Guo, 2024). These mixed accounts challenge binary classifications of adopters as either enthusiastic or resistant. The more relevant distinction concerns whether employees possess adequate control, competence, time, and institutional clarity to absorb new demands. Where these resources are missing, repeated verification and policy ambiguity can convert an initially helpful tool into sustained cognitive and emotional load.

The broader health-impairment evidence linked AI-related anxiety and technostress with diminished well-being, burnout, insecurity, turnover mechanisms, or constrained career growth (Gusti et al., 2026; Jin et al., 2026; Shekhar & Saurombe, 2026). Some challenge stressors were associated with resource gain, but hindrance stressors produced loss, particularly when employees perceived opacity, surveillance, displacement, or limited organisational support. The evidence therefore supports differentiated technostress rather than the assumption that every technology demand is harmful.

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Boundary conditions and integrated synthesis

Across the 18 reports, six boundary conditions repeatedly determined how GenAI was experienced: AI literacy, autonomy, task–technology fit, leadership and organisational support, workload recognition, and governance clarity. These conditions act at different levels. Literacy and appraisal shape whether an employee can use and scrutinise output; autonomy allows tasks to be redesigned; support and leadership provide learning and psychological resources; workload recognition prevents invisible verification from being ignored; and governance reduces uncertainty over data, authorship, and acceptable use.

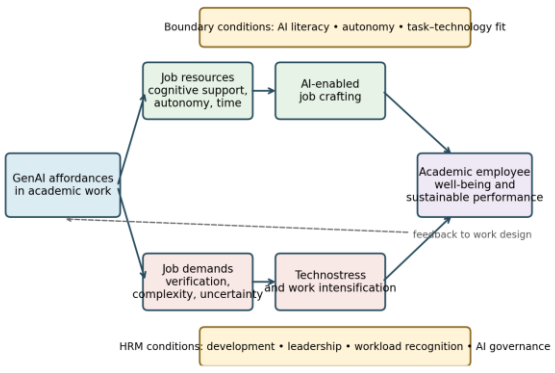
The integrated framework consequently does not position GenAI as a direct cause of well-being. Affordances become resources through appraisal and active crafting, whereas verification, complexity, uncertainty, insecurity, and escalating expectations may become demands through technostress. Both processes can occur concurrently and can change over time as tools, tasks, and policies evolve. The arrows in Figure 2 represent evidence-informed propositions, not effect estimates or empirically tested mediation paths.

Table 3. Integrated synthesis of the dual pathways

Path	GenAI conditions	Mechanism	Outcome	Boundary conditions
Resource pathway	Cognitive assistance; time saving; autonomy; information access	Approach job crafting; engagement; professionalism	Happiness, energy, sustainable performance	AI literacy; autonomy; task fit; mindfulness; support
Demand pathway	Verification labour; complexity; uncertainty; surveillance; insecurity	Technostress; overload; dependency; avoidance/alienation	Stress, burnout, depletion, impaired well-being	Workload recognition; clear rules; resilience; responsible governance
Simultaneous pathway	Efficiency gains coexist with new accountability work	Task-level appraisal changes over time	Mixed emotions and conditional well-being	Performance expectations and managerial response

Source: Processed Data (2026)

Figure 2. HRM-oriented dual-pathway framework



Source: Authors' synthesis (2026).

The integrated framework does not treat GenAI as a direct cause of well-being. Affordances are converted into resources through employee appraisal and crafting, whereas new demands may produce technostress and work intensification. AI literacy, autonomy, task–technology fit, development, leadership, workload recognition, and governance shape both pathways. The arrows represent evidence-informed propositions, not effect estimates or tested causal mediation.

DISCUSSION

Theoretical contribution

The first theoretical contribution is to position GenAI within a sociotechnical work system rather than treat it as an independent productivity intervention. The findings show that occupational consequences arise from the interaction of affordances, task characteristics, employee capability, professional accountability, performance expectations, and governance. This extends JD–R reasoning by demonstrating how a single technology can create resource gain and demand escalation within the same task. Faculty well-being findings are consistent with this conditional view: perceived usefulness relates to positive functioning, while verification, uncertainty, and anxiety prevent a uniformly beneficial interpretation (Cambra-Fierro et al., 2025; Liu et al., 2025).

The second contribution is to integrate job crafting and technostress as complementary mechanisms. Job crafting explains the motivational process through which employees reorganise AI-enabled work, whereas technostress explains how complexity, overload, uncertainty, insecurity, and accountability costs can impair health. This integration extends workplace crafting studies by specifying the demand pathway that may accompany resource conversion (Dong et al., 2026; Liu et al., 2026). It also explains why selective non-use can constitute protective boundary management rather than simple resistance when output reliability is weak or professional risk is high.

The third contribution is evidential calibration. Direct academic evidence strongly supports workload change, anxiety, dependency, mixed emotion, technostress, and conditional well-being. Evidence for the job-crafting pathway among lecturers is less direct and relies partly on workplace bridge studies. The proposed framework is therefore empirically grounded but not empirically verified as a complete causal model. This distinction avoids converting a plausible cross-literature mechanism into an unsupported claim of mediation.

The synthesis also aligns with AIBPM scholarship on the double-edged nature of digital work. Tinake and Tamima (2026) show that digital flexibility can increase autonomy while blurred boundaries increase burnout risk, and Suhartini and Syariati (2026) report that self-regulation and agility can coexist with technostress. The present review extends those arguments into GenAI-enabled academic employment by identifying job crafting and verification labour as specific conversion mechanisms. It further qualifies broad claims that AI improves HRM efficiency and future work systems (Shouran & Ali, 2024, 2025): efficiency is sustainable only when human oversight, workload, capability, and well-being are governed together.

Implications for HRM in higher education

HRM should govern GenAI as a work-design and employee-well-being issue rather than only as educational technology adoption. First, universities need role-specific development that combines prompting with critical evaluation, source verification, privacy, bias awareness, disclosure, and task selection. Protected learning time is essential because capability development is itself work. Peer communities can help

employees compare practices and reduce isolated trial-and-error, but participation should not become an additional unrecognised demand.

Second, performance management must recognise demand displacement. Managers should not assume that faster initial production justifies automatic increases in teaching, publication, or administrative targets. Workload systems should account for verification, ethical review, correction, and documentation. Leaders also need to preserve professional discretion: lecturers should be able to decline GenAI for confidential, high-stakes, or pedagogically unsuitable tasks without being labelled resistant to innovation.

Third, responsible governance should combine data-protection rules, authorship and disclosure standards, approved-use cases, escalation channels, and periodic psychosocial-risk monitoring. Adoption metrics should be complemented with indicators of workload, recovery, confidence, error correction, and perceived control. These measures operationalise the broader HRM principle that AI value depends on alignment between technology and people systems. They also respond to AIBPM findings that human oversight and ethical governance remain necessary even when AI improves HR efficiency (Shouran & Ali, 2024).

Finally, implementation should be treated as an iterative employment intervention. HR units, academic leaders, information-technology teams, research-integrity officers, and employee representatives should jointly review how particular tasks change. A task-level review is more actionable than a universal adoption policy because risks differ between brainstorming, formative feedback, assessment, confidential research, and personnel decisions. The practical objective is not maximum use, but sustainable use that produces genuine resource gains without transferring hidden costs to academic employees.

CONCLUSION

GenAI can empower and intensify academic work at the same time. It supports well-being when cognitive and temporal affordances are converted into job resources through purposeful redesign, adequate capability, autonomy, and support. It undermines well-being when verification labour, complexity, uncertainty, dependency, insecurity, and escalating expectations create technostress. The main conclusion is therefore conditional: sustainable outcomes depend less on access to the technology than on the configuration of task, employee capability, professional accountability, and organisational governance.

The review contributes an HRM-oriented dual-pathway framework linking GenAI to academic employee well-being through evidence-informed job-crafting and technostress mechanisms. Universities should develop critical AI capability, preserve discretion, recognise verification workload, align performance expectations with responsible practice, and monitor psychosocial risk. Future research should test the framework with time-separated, longitudinal, or experimental data from lecturers who use GenAI in actual work. Until such evidence is available, the framework should guide diagnosis and policy design rather than be treated as a proven causal model.

LIMITATION

This review has five limitations. First, the evidence base is recent, terminology is unstable, and many direct academic studies are cross-sectional or adoption-oriented. Second, 23 of 41 sought reports were not retrieved, creating a possible retrieval bias; their metadata were retained for audit, but their findings and quality were not inferred. Third, Scopus was the only completed database source, so relevant studies indexed

elsewhere may have been missed. Fourth, workplace bridge studies strengthen mechanism development but cannot establish that identical processes occur among lecturers. Fifth, heterogeneous outcomes and designs supported explanatory synthesis rather than pooled effect sizes, prevalence estimates, or causal mediation claims. These limitations require cautious interpretation and make direct longitudinal research in academic employment a priority.

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