Antecedents of sustainable generative AI use among HEIs employees: examining net benefits through the lens of IS success and innovativeness

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Abstract

Purpose – This study aims to explore and identify key antecedents influencing the sustainable use of Generative artificial intelligence (GenAI) among employees within higher education institutions (HEIs) in the UK, utilizing the DeLone and McLean Information Systems Success Model (DMISSM) extended with the construct of individual innovativeness. Furthermore, it examines the resulting net benefits, including enhanced competence, decision quality and productivity.

Design/methodology/approach – A quantitative, cross-sectional research design was adopted. Data were collected from 242 employees working in academic and administrative roles within UK higher education (HE), using an online survey. Partial least squares-structural equation modeling (PLS-SEM) was employed to test the hypotheses and validate the proposed conceptual framework.

Findings – The study confirms that system and information quality, user satisfaction and individual innovativeness significantly influence employees' sustainable use of GenAI tools. Sustainable use, in turn, has a

substantial positive impact on employees' net benefits, particularly in terms of productivity, competence and

decision-making quality.

Originality/value – This research makes novel theoretical contributions by integrating innovativeness into the

DMISSM, offering fresh insights into GenAI adoption dynamics within HE. Practically, the findings underscore

crucial considerations for HEIs aiming to effectively leverage GenAI to improve employee performance and

achieve broader Sustainable Development Goals (SDGs).

Keywords Generative AI, Sustainable use, IS success model, Net benefits, Higher education institutions,

Sustainable Development Goals

Paper type Research article

1. Introduction

The rapid evolution and widespread adoption of artificial intelligence technologies have fundamentally transformed numerous sectors, and the higher education (HE) sector is no exception, experiencing particularly significant changes in recent years (Dwivedi et al., 2021; Mariam et al., 2024). Generative artificial intelligence (GenAI), characterized by its ability to create original content across various modalities, represents a pivotal advancement with far-reaching implications for educational institutions and their employees (Kasneci et al., 2023). However, its outputs are inherently shaped by the quality and scope of the training data it has been exposed to. As the UK's HE sector navigates this technological revolution, understanding the factors that influence the sustainable use of GenAI that reflects the HE institute employees' sustained motivation to persist, engage with and integrate the GenAI into their routines beyond its initial adoption broader societal impact (Zawacki-Richter et al., 2019; Zhai et al., 2021).

The United Nations' Sustainable Development Goals (SDGs) provide a comprehensive framework for assessing the multifaceted impacts of GenAI across diverse domains (Gupta et al., 2021). Research by Vinuesa et al. (2020) reveals that AI technologies, including GenAI, have the potential to enable the achievement of approximately 79% of SDG targets. Specifically in HE, the integration of GenAI delivers tangible benefits to faculty and staff by automating routine administrative tasks such as grading, scheduling and handling student inquiries. This automation not only enhances teaching efficiency but also improves HE employees' net benefits in terms of competency, decision-making and productivity, thereby supporting quality education (SDG 4) (United Nations, 2023). Additionally, GenAI adoption promotes innovation in institutional practices (aligning with SDG 9) and fosters greater equity by democratizing access to educational resources (supporting SDG 10) (United Nations, 2023). Empirical evidence further indicates that through the automation of routine tasks, academic staff experience significant improvements in job satisfaction and work-life balance (Chopra and Sharma, 2020). Moreover, by facilitating personalized learning experiences and reducing educator burnout, GenAI empowers higher education institutions (HEIs) to innovate continuously while adhering to ethical, sustainable practices that align with the broader objectives of the SDGs (Omri, 2020; Strielkowski et al., 2024).

The integration of GenAI into the HE sector has the potential to significantly enhance employee productivity by automating repetitive tasks, enabling personalized learning experiences and fostering data-driven decision-making. GenAI tools, such as ChatGPT and other large language models, can assist faculty and administrative staff in generating course content, grading assignments and managing administrative workflows, thereby freeing up time for more strategic and creative tasks (Bobula, 2024). For instance, AI-powered systems can analyse vast amounts of student data to provide actionable insights, helping educators tailor their teaching methods to meet diverse learning needs (Holmes et al., 2022). Additionally, GenAI can streamline communication by automating responses to student inquiries and generating reports, reducing the administrative burden on staff (Zawacki-Richter et al., 2019). By leveraging these technologies, HEIs can not only improve operational efficiency but also foster innovation and improve employees' net benefit and therefore the overall educational outcomes.

Existing studies on technology adoption in education have largely focused on student outcomes, neglecting the role of institutional employees as critical stakeholders in driving sustainable innovation (Tian et al., 2024; Wang et al., 2024; Zawacki-Richter et al., 2019). According to the surveyed literature and to the best of the authors' knowledge, no research has examined the antecedents affecting the sustainable use of GenAI and its impact on employees' net benefits (competence, decision quality and productivity), which makes this research one of the first attempts to explain the antecedents and impact of suitable GenAI use on HE employees' net benefit. Therefore, this research aims to fill this gap in the literature by integrating and extending a well-known theory, DeLone and McLean Information Systems Success Model (DMISSM) (DeLone and McLean, 2003), with innovativeness (Rogers, 2003), to explain the determinants influencing UK's HE sector employees' sustainable use of GenAI and its impact on employees' net benefit. This is accomplished by collecting data from UK to understand the antecedent of sustainable use of GenAI applications and go beyond to understand its impact on employees' net benefits within the UK HE sector.

2. Literature review

GenAI refers to AI systems that autonomously create original content by learning patterns from extensive datasets. These systems emulate the style and structure of their training data, fostering innovation and automation across various industries. GenAI has markedly enhanced workforce performance and productivity across diverse industries worldwide by automating routine tasks, streamlining workflows and facilitating more informed decision-making. In corporate environments, the deployment of AI-powered virtual assistants and automated report generation systems has effectively reduced administrative burdens, thereby enabling employees to focus on strategic initiatives (Brynjolfsson et al., 2025). In healthcare, GenAI tools support clinical decision-making and research by rapidly processing extensive medical records and scientific literature, expediting diagnostic procedures and enabling personalized treatment protocols (Bhuyan et al., 2025; Edwin Hillary et al., 2024). Similarly, in the financial sector, advanced AI models contribute to real-time fraud detection and risk assessment, which improve operational efficiency while minimizing errors in compliance and transaction processing (Remolina, 2024; Zada et al., 2024). In educational settings, adaptive learning systems powered by GenAI tailor instructional content to individual student needs, thereby enhancing teaching effectiveness and learner engagement (Bobula, 2024; Mulyani et al., 2025). Furthermore, marketing and creative industries harness AI-driven content generation to produce high-quality campaigns and communications efficiently, bolstering overall workforce productivity and fostering innovation (Islam et al., 2024; Totlani, 2023). Collectively, these advancements underscore GenAI's transformative impact on employee productivity and performance on a global scale.

While other sectors have begun integrating generative AI (GenAI) to enhance performance and decision-making, HEIs present a distinct institutional environment. HEIs are increasingly expected to align with the UN SDGs (United Nations, 2016), placing emphasis not only on technological innovation but also on sustainability, inclusiveness and ethical deployment. These unique dynamics make it essential to investigate the quality, innovativeness and sustainable use of GenAI within HEIs as a standalone context, especially in relation to competence, decision quality and productivity.

3. Model development and hypotheses

The present study developed a theoretical model based on the updated DMISSM (DeLone and McLean, 2003) to explain the antecedent factors affecting the sustainable use of GenAI and their impact on the HE sector's employees' net benefits. The updated DMSIM has been widely used in research – which is a reason of choosing this model – to assess information systems (IS) success within different regions and contexts (Al and Shamma, 2024; Al-

fadhli et al., 2018; Alotaibi and Alshahrani, 2022), focusing on six key dimensions: quality (system, information and service), use, user satisfaction and net benefits, and this is another reason for using the updated DMISSM as underpinning theory, as it focuses on the technology quality. However, in this study's theoretical model, researchers have omitted the service quality factor, as the technology under investigation is GenAI and the service provided is the information given to users. Accordingly, the service quality is not important in this context. On the other hand, the DMISSM has only focused on the technological characteristics, such as quality, and has neglected the individual traits, such as innovativeness and its impact on the technology use (Rogers, 2003). A study by Aldholay et al. (2022) asserted the importance of innovativeness in technology acceptance and use.

In this study, it is expected that net benefits of employees of the HE sector in the UK will be affected by the sustainable use of GenAI, which itself is shaped by the quality, satisfaction and innovativeness as depicted in Figure 1. Since GenAI is relatively novel, it is believed that using those factors would provide an in-depth understanding of the sustainable use of GenAI and the net benefits of the UK's HE sector employees

3.1 Quality (system, and information)

The IS advancement has galvanized researchers to refine frameworks that enhance utility and quality, thereby unlocking the field's growth potential (Aldholay et al., 2019). The DMISSM by DeLone and McLean (2003) posits that quality aspects influence IS use. In this research, quality is conceptualized as a second-order construct comprising system quality and information quality, each exerting distinct influences on continuous intention and use of the IS system (Alshammari and Alshammari, 2024; Li and Shang, 2020). In this research, system quality is defined as the extent to which the users of a GenAI think that it is easy to use and flexible to interact with, and that the interaction with the GenAI is clear. Further, information quality was characterized by the extent to which HE sector employees believe that GenAI information provided is up-to-date, accurate, relevant, comprehensive and organised. Previous extensive literature has asserted the importance of quality to predict the continuous use of IS and sustainable use in different contexts and applications (Chen et al., 2024; Mun and Hwang, 2024; Song et al., 2023). In the context of this study, the following hypothesis is proposed:

H1. Quality has a positive effect on sustainable use of GenAI among employees within the higher education sector in the UK.

3.2 User satisfaction (STS)

User satisfaction is widely recognized as a pivotal factor in assessing the successful adoption of new IS and has consequently been extensively utilized as a key indicator within the IS domain (Aldholay et al., 2019). Xinli (2015) has defined user satisfaction as the degree to which a consumer sees a system to be helpful. Empirical studies in IS research have established that user satisfaction, stemming from favourable system experiences, serves as a primary predictor of continuance intention to use (Baig and Yadegaridehkordi, 2025). The academic literature robustly supports a positive correlation between user satisfaction and continuance intention to use, as evidenced by multiple studies (Budhathoki et al., 2024; Chen et al., 2023). In the present investigation, the sustained and continuous intention to utilize GenAI among HE employees is significantly influenced by the consistent recognition of its positive effects on their work tasks, which accordingly will lead to a long-term integration of GenAI into their workflows. Hence, the following hypothesis is proposed:

H2. GenAI user satisfaction has a positive effect on sustainable use of GenAI among employees within higher education sector in the UK.

3.3 Innovativeness (INN)

The concept of innovativeness, pivotal to technology adoption research, was first operationalized in IS literature by (Agarwal, 2000), who identified it as a critical driver of engagement with emerging technologies. Rooted in Rogers', 2003) theory, innovativeness is defined as an individual's propensity to embrace and experiment with novel technological solutions. This personal trait reflects a broader orientation toward risk-taking and adaptability, wherein employees with higher innovativeness demonstrate greater readiness to integrate new tools into their workflows (Khan et al., 2022). Empirical studies posit that innovativeness cultivates positive attitudes toward technological advancements, accelerating their adoption and continuous adoption in professional settings (Aldholay et al., 2022). Seminal work by Abubakre et al. (2022) and Yang and Wu (2021) further emphasizes its role in shaping both the comprehension and utilization of cutting-edge systems. Building on this foundation, the present study investigates innovativeness as an antecedent of sustainable use of GenAI for academic and administrative employees within the HE sector to drive their net benefits. Hence, the following hypothesis is proposed:

H3. Innovativeness has a positive effect on sustainable use of GenAI among employees within the higher education sector in the UK.

3.4 Sustainable use (SUST)

The construct of continuance intention and use (sustainable use), grounded in the expectation-confirmation model (ECM) and central to IS research, is defined as a user's sustained motivation to persist with a technology after its initial adoption (Bhattacherjee, 2001). In the literature of IS, this

construct was studied as a dependent variable within different contexts (Mun and Hwang, 2024; Wu and Xie, 2024). In this study, the researchers operationalised the sustainable use as to what extent employees within the HE sector believe that they will continue and sustain their usage of GenAI applications. The model in this research is extended to test the relation between sustainable use and net benefits among employees of the HE sector. Therefore, the following hypothesis is formulated:

H4. Sustainable use of GenAI has a positive effect on employees' net benefit among employees within the higher education sector in the UK.

3.5 Net benefits (productivity, competence and decision quality) (net benefits)

Net benefits are defined as "the extent to which IS are contributing to the success of individuals, groups, organizations, industries, and nations, for example, improved decision making, improved productivity" (DeLone and McLean, 2016). In the context of this study, net benefits refer to the perceived success of HE sector employees in terms of competence, decision quality and productivity of using GenAI. Prior research has measured net benefits through multiple indicators (Daniel et al., 2025; Mahmud et al., 2023). Building on this foundation, the current study advances the understanding of IS outcomes – specifically GenAI – by proposing a refined, multi-

dimensional framework for net benefits. Specifically, the construct is disaggregated into three distinct dimensions, competence, decision quality and productivity, each operationalized with its own set of indicators. This granular approach enhances the model's explanatory capacity, enabling a more nuanced analysis of how GenAI contributes to individual success. By delineating these dimensions, the study not only addresses gaps in prior conceptualizations but also provides deeper insights into the mechanisms through which net benefits manifest in practice.

4. Research method

4.1 Sampling and data collection

This cross-sectional study, conducted from February to March 2025, evaluates the theoretical model by employing a web-based survey using MS Forms, targeting UK's HE sector's employees (academic and administrative). UK as a context was chosen as the report shows that at least 42% of the educators have used GenAI in their work for either academic or administrative tasks, according to the Open Innovation Team and Department for Education (2024). The data collection method used is non-probability purposive sampling, as there was no sampling frame (Sekaran and Bougie, 2013). Data was collected through the professional data collection platform Prolific (https://www.prolific.com/) with certain criteria: 1. working in the HE sector in the UK, 2. used/using GenAI in their work, to make sure they fit within the study population. The sample was selected as highly educated individuals are likely early IT adopters (Al-Sharafi et al., 2022). A link to the online survey was uploaded to the Profilic platform targeting potential respondents of 1320; a sample size of (N 5 286) responses was collected, of which 44 cases were deleted as they responded that they were either not working in the HE sector in the UK or had not used GenAI. The final used sample size (N 5 242), which is deemed adequate for analysis, meets the recommended threshold (Roscoe, 1975). Sample size for multivariate data analysis should be 10 times greater than the number of variables. According to Hair et al. (2014), researchers can use software like G*Power to define the minimum sample size. This research found that the minimum sample size recommended by G*Power for this study is 80 subjects with 0.80 statistical power (Faul et al., 2007).

4.2 Instrument development

To establish construct validity and reliability, measurement items were derived through minor modifications from empirically validated scales in literature. Hence, quality (system and information) items were adopted from Lin and Wang (2012) and Mohammadi (2015); user satisfaction and sustainable use measurements were adopted from Al-Sharafi et al. (2022), net benefits measuring items were assessed based on the scale proposed by Haddad et al. (2019). Adapted items used a 5-point Likert scale (1 5 strongly disagree to 5 5 strongly agree), aligned with Al-Sharafi et al. (2023) for simplicity and reduced respondent confusion.

4.3 Data analysis

Statistical analysis has long served as a cornerstone for exploration, development and validation of experimental findings. The proliferation of these techniques has been catalysed by advancements in computational technologies (Hair et al., 2011, 2017). To validate the research model and test the proposed hypotheses, this study employed partial least squares-

structural equation modelling (PLS-SEM), mirroring methodologies utilized in prior investigations (Mutahar et al., 2022a, b). PLS-SEM was selected to elucidate the relationships between predictors and their impact on the sustainable use and net benefits of GenAI applications. The complexity of the model, characterized by a high number of indicators, necessitated the use of variance-based PLS-SEM (Al-Emran et al., 2019). PLS-

SEM demonstrates robustness against non-normal data distribution, reinforcing its suitability for this research (Hair et al., 2017; 2014).

5. Results

5.1 Respondents' demographics description

The respondent demographic profile comprises a diverse group. The sample (N 5 242) comprised HE employees, with a gender distribution of 56.6% female, 40.9% male and 2.4% non-binary/undisclosed. Most participants (69.5%) were aged 26–45, followed by 46–55 (17.4%), over 55 (7.9%) and 18–25 (5.4%). Educationally, 59.5% held postgraduate degrees, 30.2% undergraduate degrees, and 10.4% diplomas or other qualifications. Roles were evenly split between academic (51.7%) and non-academic staff (48.3%), with 84.7% employed full-

time, 12.4% part-time and 2.9% on contractual terms. This demographic diversity ensures a representative cross-section for analysing perspectives within the target population.

The measurement model was rigorously assessed for reliability and validity of reflective-

reflective first-order and second-order constructs (Hair et al., 2021; Ramayah et al., 2018). Specifically, net benefits (COM, PRD, DQ) and quality (INFQ, SYSQ) were operationalized as second-order constructs. The psychometric properties of the constructs, encompassing factor loadings, Cronbach's alpha (CA), composite reliability (CR) and average variance extracted (AVE), are detailed in Tables 1 and 2 (Becker et al., 2023; Hair et al., 2021). Factor loadings for all items exceeded the recommended threshold of 0.708, indicating strong indicator reliability. CA values for the constructs ranged from 0.757 to 0.943, surpassing the benchmark of 0.70. CR values further validated construct reliability, ranging from 0.760 to 0.932, well above the recommended threshold of 0.70 (Hair et al., 2021; Ramayah et al., 2018). These results confirm the internal consistency and reliability of the constructs.

Convergent validity was assessed using the AVE, which measures the extent to which indicators explain the variance of their respective constructs. AVE values for all constructs ranged from 0.660 to

0.854, exceeding the recommended threshold of 0.50 (Hair et al., 2021; Ramayah et al., 2018). This demonstrates that the constructs effectively capture shared variance among their indicators, affirming convergent validity.

Discriminant validity was evaluated for first-order and second-order constructs using the Fornell–Larcker criterion and the Heterotrait-Monotrait (HTMT) ratio (Henseler et al., 2015). These approaches confirm that each construct represents a distinct concept, reducing the risk of multicollinearity or conceptual overlap. According to the Fornell–Larcker criterion, discriminant validity is established when the square root of a construct's AVE exceeds its correlations with other constructs (Becker et al., 2023; Lim, 2024). As shown in Tables 2 and 4, diagonal values reflect the square roots of AVEs, while off-diagonal values show inter-

construct correlations.

The HTMT ratio offers a stricter evaluation of discriminant validity by comparing average correlations between constructs against those within constructs, with values below 0.90 indicating satisfactory validity (Henseler et al., 2015). As shown in Table 2, all HTMT values for first-order constructs fall below this threshold, confirming strong discriminant validity.

For second-order constructs, discriminant validity was evaluated using the Fornell– Larcker criterion, revealing that the AVEs for Net Benefits (0.881) and Quality (0.874) exceeded their inter-construct correlation (0.712), as displayed in Table 4. This confirms that the constructs are distinct yet related, as anticipated for reflective-reflective type 1 models. Additionally, the HTMT ratio for second-order constructs was calculated, yielding a value of 0.918, slightly above the 0.90 threshold. However, this minor deviation is acceptable given the hierarchical nature of reflective-reflective second-order constructs, which inherently involves some conceptual overlap.

5.3 Structural model assessment and hypothesis testing

The structural model was rigorously assessed to evaluate the hypothesized relationships between the constructs, ensuring both statistical significance and practical relevance (see Figure 2). The analysis involved examining path coefficients, t-values, p-values, confidence intervals, variance inflation factors (VIF), effect sizes (f-square) and the coefficient of determination (R-square) (Becker et al., 2023; Hair et al., 2021). These metrics collectively provide a comprehensive understanding of the model's explanatory power and the strength of the proposed relationships.

Prior to hypothesis testing, collinearity among predictor constructs was evaluated to ensure the absence of multicollinearity issues that could undermine the robustness of the results. As indicated in Table 3, all VIF values were below the threshold of 3.33, confirming that multicollinearity was not a concern in the structural model. Then, the bootstrapping technique with 5,000 resamples was employed to compute path coefficients, t-values and associated p-values for each hypothesized relationship. The first hypothesis posited a positive relationship between Quality and Sustainable Use. The results revealed a path coefficient of 0.180, with a t-value of 2.825 and a p-value less than 0.05, indicating statistical significance. The 95% confidence interval (0.052–0.305) further confirmed the robustness of this relationship. Consequently, the hypothesis was supported. The effect size for this relationship was 0.041, suggesting a small but meaningful contribution of quality to sustainable use.

The second hypothesis examined the influence of User Satisfaction on Sustainable Use. The analysis yielded a path coefficient of 0.581, with a highly significant t-value of 10.736 and a p-value <0.001. The confidence interval (0.470–0.683) excluded zero, affirming the strength of this relationship. The effect size was 0.404, indicating a large practical impact of user satisfaction on sustainable use. Thus,

the hypothesis was strongly supported. The third hypothesis explored the relationship between Innovativeness and Sustainable Use. The path coefficient was estimated at 0.123, with a t-value of 2.792 and a p-value of 0.005. The confidence interval (0.042–0.216) provided additional evidence of the relationship's significance. The effect size was 0.033, reflecting a small but notable contribution of innovativeness to sustainable use. This hypothesis was also supported. The final hypothesis investigated the impact of Sustainable Use on Employee Net Benefits. The results demonstrated a path coefficient of 0.732, with an exceptionally high t-value of 19.432 and a p-value of 0.000. The confidence interval (0.650–0.799) further validated the robustness of this relationship. The effect size (f-square) was 1.157, indicating a very large practical impact of sustainable use on employee net benefits. This hypothesis was unequivocally supported.

The coefficient of determination (R 2) values highlighted the explanatory power of the model. For SUST, the R 2 value was 0.587, indicating that 58.7% of the variance in sustainable use is explained by the predictors quality, user satisfaction and innovativeness. Similarly, the R 2 value for Employee Net Benefits was 0.536, suggesting that 53.6% of the variance in net benefits is accounted for by sustainable use. These substantial R 2 values underscore the model's strong explanatory capacity (Chin, 2010). Besides, the effect sizes (f 2) were computed to assess the practical significance of each predictor's contribution to the dependent constructs

(Cohen, 1988, 2013; Hair et al., 2016). The findings revealed that AI User Satisfaction had a large effect size (f 2 5 0.404) on sustainable use, while Quality and Innovativeness exhibited small effect sizes (f 2 5 0.041 and 0.033, respectively). Notably, Sustainable Use demonstrated a very large effect size (f 2 5 1.157) on employee net benefits, highlighting its pivotal role in driving positive outcomes (see Table 5).

6. Discussion

The aim of the study is to examine the antecedents and the impact on the net benefits of sustainable use of GenAI among the HE sector's employees. The proposed model was grounded on the DMISSM model with the consideration of an individual characteristic: individual innovativeness. For this study, data were collected from employees in the HE sector who actually used/using GenAI in their work in the UK The analysis validated the proposed model, demonstrating a robust fit as all factors significantly influenced the sustainable use of GenAI applications and net benefits, thereby establishing a coherent framework to explain these outcomes.

The findings underscore the critical role of quality, specifically system quality and information quality, in driving the sustainable use of GenAI applications among HE sector employees, aligning with prior studies (Bakar and Melan, 2018; Mun and Hwang, 2024). Practically, this means that university IT leaders should prioritize GenAI platforms with attributes such as intuitive user interfaces, real-time feedback and consistent information accuracy. These features

are not just technical preferences but strategic levers for sustained usage across roles.

Similarly, user satisfaction emerged as a significant predictor of sustainable use, corroborating existing literature (Al-Sharafi et al., 2022; Baig and Yadegaridehkordi, 2025). When HE employees perceive GenAI tools as valuable and user-friendly, their satisfaction fosters continued engagement, reinforcing the importance of GenAI application quality with user expectations. This suggests that regular usability testing and refinement cycles should be institutionalized to preserve high satisfaction levels, which in turn fuel long-term adoption.

The study also confirmed innovativeness as a pivotal factor in sustainable GenAI use, supporting earlier work (Novitasari and Suryandari, 2022). Employees who proactively embrace technological advancements exhibit stronger tendencies to integrate GenAI into workflows, highlighting the interplay between individual adaptability and available technological uptake supported by the HEI. Institutions can operationalize this insight by offering targeted training in prompt engineering and ethical AI use, empowering innovative employees to act as internal GenAI champions.

Furthermore, sustained GenAI use significantly enhances net benefits, particularly in terms of competence, decision quality and productivity. This aligns with the proposition that repeated, purposeful engagement with GenAI tools sharpens employees' skills, optimizes data-driven decisions and streamlines task execution. In practice, these improvements contribute to faster turnaround in grading, more precise student advising and administrative process optimization. Theoretically, the study not only affirms the DMISSM model but meaningfully extends it by introducing individual innovativeness as a parallel antecedent to quality and satisfaction. This addition is supported by both statistical significance and conceptual logic, confirming the importance of employee traits alongside system factors in technology adoption frameworks. The model demonstrates that sustainable use serves as a key mediator between upstream variables and downstream outcomes, offering a process-based understanding of value realization from GenAI.

Contextually, these results take on added relevance amid growing digital transformation pressures in HE. HEIs face demands to reduce workloads, personalize learning experiences and demonstrate sustainability alignment. By showing how GenAI addresses these exact needs, particularly through gains in productivity and decision quality, this study affirms its strategic value. These outcomes also contribute to multiple SDGs, notably SDG 4 on Quality Education and SDG 9 on Innovation. However, disparities in GenAI access between academic and non-academic staff, or across departments with differing digital competencies, highlight equity concerns linked to SDG 10.

Conclusively, to maximize the sustainable use of GenAI and its associated net benefits, two interdependent factors are critical. First, HE sector employees must cultivate proactive engagement with emerging technologies, fostering a mindset that prioritizes innovativeness and adaptability. Second, HE institutions must prioritize GenAI applications with robust system quality and information quality, as these directly shape long-term user adoption. This includes investing in technologies that support real-time collaboration, multilingual processing and secure data integration. By leveraging GenAI with institutional investments in high-quality tools, HEIs can amplify competence, productivity, decision quality and overall workflow efficiency, ensuring that net benefits scale proportionally with sustained technological integration.

7. Conclusion

The study investigates the antecedents and impact of GenAI on HE employees' sustainable use and net benefits in the UK, with a focus on promoting the United Nations' SDGs. By extending DMISSM with innovativeness, this research provides valuable insights into the dynamics of GenAI adoption, utilization and its outcomes. Below, the theoretical contributions, practical implications, limitations and future research directions are discussed.

7.1 Theoretical contributions

This study makes several significant contributions to the existing literature on IS, artificial intelligence and sustainability. First, it extends the DMISSM framework by incorporating innovativeness as a critical antecedent of sustainable use. This addition highlights the role of novelty and creativity in driving the adoption and sustained use of GenAI systems, thereby enriching the theoretical foundation of DMISSM. Second, the study underscores the mediating role of sustainable use in linking system quality, user satisfaction and innovativeness to employee net benefits. This mediation emphasizes the importance of consistent and effective use of AI tools in achieving long-term organizational goals. Third, the findings contribute to the growing body of knowledge on the intersection of AI and sustainability by demonstrating how GenAI can be leveraged to promote the SDGs in HE. Finally, the robust empirical validation of the proposed framework using PLS-SEM provides a methodological contribution, offering a replicable approach for future studies in this domain. Future researchers are encouraged to examine how these constructs behave across different cultural and linguistic contexts, especially in non-Anglophone HEIs, using mixed methods to capture nuanced dimensions of innovativeness.

7.2 Practical implications

The findings of this study offer several actionable insights for practitioners, policymakers and HE institutions. First, the results highlight the importance of designing high-quality GenAI systems that prioritize both information quality and service quality. IT directors should focus on features such as uptime reliability, clear conversational interfaces and up-to-date content curation. These features were found to have a measurable impact on sustained use. Second, fostering a culture of innovativeness is crucial for encouraging employees to explore and integrate novel AI-driven solutions into their workflows. Institutions should offer focused training programs on prompt engineering, responsible AI use and critical evaluation of AI-generated content. These programs can amplify the productivity and leadership potential of employees with high innovative capacity. Third, the study underscores the pivotal role of user satisfaction in sustaining the use of GenAI systems. Policymakers should adopt participatory design approaches and include end users in pilot evaluations, feedback loops and system revisions to maintain high satisfaction levels. Fourth, the positive impact of sustainable use on employee net benefits, including productivity, competence and decision quality, highlights the need for organizations to invest in strategies that promote consistent and meaningful engagement with AI tools. Examples include role-specific GenAI integrations for teaching staff, administrative task automation for registrars and custom dashboards for deans and directors. Fifth, to ensure responsible adoption and equitable impact, HEIs must address potential disparities in GenAI access and capability across departments and job roles. This is particularly relevant to SDG 10, which focuses on reducing institutional inequality. Ensuring uniform access to training and tools is essential.

Finally, the study's emphasis on the alignment of GenAI adoption with sustainability goals provides a roadmap for institutions seeking to balance technological advancement with societal responsibility.

This roadmap can be structured into three stages: policy and ethical alignment, workforce capacity building and digital infrastructure investment. Each stage includes actionable steps such as forming GenAI task forces, incentivizing innovation and implementing secure cloud-based AI tools.

7.3 Limitation and future work

While this study provides valuable insights into the sustainable use of GenAI in HE institutions, several limitations should be acknowledged. First, the research focuses exclusively on employees within UK HEIs. This limits the generalizability of the findings to other countries or educational systems. Future studies should validate the proposed model in non-Anglophone and culturally diverse contexts, as the perception of system quality and innovativeness may vary across institutional cultures and regions. A mixed-methods design could capture deeper qualitative nuances around these dimensions.

Second, the use of a cross-sectional research design restricts the ability to observe dynamic behavioral changes over time. Longitudinal studies are recommended to examine how GenAI use evolves with growing familiarity, changes in institutional policy and shifting educational roles. Such studies could also assess long-term impacts on employee performance and organizational outcomes. Third, the current study captures employee net benefits using self-

reported perceptions, which may be subject to common method bias. Future research could incorporate objective performance metrics such as grading turnaround times, student feedback quality, or administrative efficiency indicators to validate perceived benefits.

Fourth, the framework primarily examines system- and individual-level factors. Future models could be extended by including contextual and organizational variables such as leadership support, digital infrastructure and ethical governance structures. These factors may moderate or mediate the relationships identified in this study. Fifth, while the study highlights alignment with SDG goals, it does not deeply explore the equity-related tensions in GenAI implementation. Future research should examine disparities in access to AI tools and training across job roles, genders and departments to ensure inclusive digital transformation. Finally, the inclusion of constructs such as trust in AI, perceived ethical risk and resistance to AI-driven change could enhance the explanatory power of the model. These variables are especially relevant as GenAI systems become increasingly autonomous and embedded in critical academic functions.

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