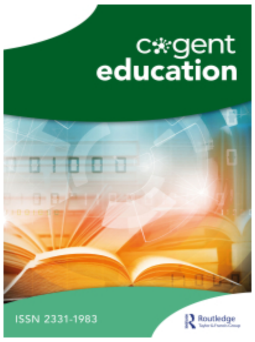

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Analysing the built environment academics' perceptions of generative AI technology on teaching and learning practice

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ABSTRACT
The study examines the influence of Generative Artificial Intelligence (GenAI) technology on teaching and learning within the built environment discipline from the perspective of academics. It explores the relationships between academics' experience, AI knowledge, willingness to adopt AI technologies and their capacity to detect student use of AI. A mixed-methods approach was employed, incorporating qualitative interviews and quantitative surveys with built environment academics. A web scraping technique was used to obtain the contact details of potential research participants for purposive sampling, resulting in a sample of 56 participants from 42 UK universities offering built environment education. Cramér's V coefficient was applied to analyse the relationships between the variables. The findings suggest that academics' experience significantly affects their adoption of AI, their preparedness to adapt assessments and their ability to detect AI use by students. Academics with broader subject expertise are more inclined to embrace GenAI and adjust teaching practices. These insights contribute to policy development for integrating GenAI into built environment pedagogy and support its wider adoption in higher education.

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Introduction

The application of Generative Artificial Intelligence (GenAI) technology in higher education is increasing rapidly, and this is driven by rising adoption among students and academics for teaching, learning and research. As GenAI tools become more integrated into educational practices, they are likely to become as ubiquitous as search engines, calculators and software. This integration promises to revolutionise various aspects of higher education, including student learning, instructional methods and assessment practices. However, the widespread adoption of GenAI raises significant concerns amid unclear regulatory guidance on its usage within higher education policies (Department for Education, 2023).

The lack of a clear regulatory ethical framework presents a major threat to the potential benefits of GenAI in teaching and learning; furthermore, the extent to which GenAI will alter educational practices remains uncertain and a major concern for stakeholders (Firth et al., 2024). This uncertainty stems from

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several factors. A major issue is the variability in learning requirements across different disciplines and educational levels which can lead to a wide variance in the impact of GenAI (Mishra et al., 2023). Additionally, the attitudes of stakeholders, including academics, students and policymakers, towards technological change can significantly influence the adoption and implementation of GenAI (Al-Zahrani, 2024; Zawacki-Richter et al., 2019). Broader social, economic, technological, legal and regulatory factors also play a critical role in shaping the integration of GenAI into higher education (Mikeladze et al., 2024; Williams, 2019). Therefore, it can be argued that there is no one-size-fits-all guidance capable of ensuring the ethical usage of GenAI across disciplines, levels of study, experience and categories of learners and academics.

Academics are central to the design and delivery of learning, shaping instructional strategies, fostering student engagement and overseeing assessment and feedback. Given their integral role, academics' perceptions and attitudes towards GenAI use in education are crucial for devising effective and sustainable frameworks for its integration into higher education. Their insights on the relevance, implications and future of GenAI are instrumental in establishing a practical and ethical foundation for its adoption. Although studies (Baek & Wilson, 2024; Firth et al., 2024; Mathew & Stefaniak, 2024; Sanchez & Aleman, 2011) have examined the impact of GenAI and other similar technologies in higher education through bibliometric analysis and student surveys, there is no existing research that specifically investigates its effects on pedagogical practices within the built environment from the perspective of academics. The built environment sector, with its inherently multidimensional and interdisciplinary nature, spans the planning, design, construction, management and maintenance of land, buildings, infrastructure and facilities. This complexity makes it a valuable model for exploration, offering insights that could inform the adoption of AI-driven pedagogical practices across other disciplines.

This study analyses the perspectives of built environment academics on the impact of GenAI on teaching practices. It examines the interplay between academics' knowledge, usage, detection capabilities, experience and evolving attitudes towards GenAI in academic settings. Understanding these perceptions is key to addressing challenges and leveraging the opportunities presented by AI-driven technologies. Academics' attitudes towards GenAI have significant implications for policy development, particularly in ensuring the ethical application of AI tools in teaching. The article posits that by understanding these perceptions, institutions can create a regulatory framework that upholds academic integrity while maintaining the quality of student learning.

Generative AI technology integration in built environment pedagogy

GenAI technologies are transforming how buildings and cities are designed, planned, constructed, managed and maintained (Sawhney & Knight, 2023). Concurrently, GenAI tools are reshaping teaching, learning, assessment, feedback and research activities (Baek & Wilson, 2024; Bearman et al., 2024; Zhang et al., 2025). As these technologies advance, it is imperative for built environment academics to understand their impact on teaching practices to ensure industry relevance, foster innovation and promote ethical and effective use.

The built environment pedagogy encompasses the methods and practices of teaching and learning focused on the design, construction, management and sustainability of the physical spaces where people live, work and interact (Cotgrave & Alkhaddar, 2006; Holdsworth & Sandri, 2014). This interdisciplinary approach integrates diverse fields, including architecture, urban planning, real estate, civil engineering, quantity surveying land surveying and facility management. It combines both theoretical and practical skills, reflecting trends seen across other disciplines in higher education (Sawhney & Knight, 2023). As a model for other fields, built environment pedagogy fosters the development of comprehensive competencies, preparing students to meet the complex challenges of the 21st century. Moreover, built environment academics' experiences vary across the subjects they teach, and understanding these differences is key to formulating a functional framework for integrating GenAI technology in higher education.

The evolution of GenAI presents both challenges and opportunities for learning and teaching in higher education. Within the framework of Bloom's taxonomy, the purpose of education is to guide learners through levels of cognitive complexity, enabling them to acquire, apply and synthesise knowledge effectively (; Sharma et al., 2023). However, the adoption and over-reliance on GenAI tools, such as ChatGPT and Claude, raise concerns regarding academic integrity, as these technologies provide significant support to students, potentially undermining this established educational process (Perkins & Roe, 2024; Timotheou et al., 2023; Wijanarko et al., 2021).

Technology integration is central to the built environment pedagogy for several reasons. First, built environment professional practice relies on both generic and specific technological tools to provide services to clients (Sawhney & Knight, 2023). Second, technology is at the forefront of higher education functions, including the planning and delivery of teaching and learning (Baek & Wilson, 2024). Technology is crucial for pedagogy, encompassing the teaching of knowledge content and professional practices within the built environment. Therefore, built environment academics must be equipped with the necessary skills in technology application, such as Building Information Modelling (BIM), Geographic Information Systems (GIS), Machine Learning, Virtual Reality (VR) concepts and Augmented Reality (AR) concepts, among other technologies capable of meeting the challenges of the 21st century (Sawhney & Knight, 2023). Similarly, built environment academics should be knowledgeable about various education technology EdTech tools, including ChatGPT, Blackboard, Kahoot, Google Classroom, Quizlet and Socrative, which support and enhance teaching and learning in higher education (Opoku & Guthrie, 2018).

Ideally, the application of technology in higher education should empower students to develop critical thinking skills, problem-solving abilities and creativity, thereby preparing them to confront diverse challenges in personal, academic and professional contexts. Yet, the use of GenAI tools that generate content may discourage active engagement with cognitive processes, leading learners to depend excessively on pre-packaged solutions. Since GenAI can perform tasks that necessitate higher-order skills – such as producing, writing, analysing, designing, evaluating and critiquing, there is a risk of diminishing creativity, reducing critical thinking and impeding deep learning (Fernandes et al., 2023; Fischer et al., 2020; Timotheou et al., 2023). Consequently, while GenAI holds the potential to enhance educational experiences, its overuse could compromise the very skills that higher education seeks to cultivate.

One of the principal challenges surrounding the integration of GenAI pertains to its ethical usage. While there is a strong likelihood that GenAI is here to stay, its significant impact on academic integrity raises concerns among numerous stakeholders. Asamoah et al. (2024) highlight that integrity issues remain the foremost threat posed by this emerging technology, particularly in relation to assessment quality and concerns about plagiarism. In this context, the effectiveness and accessibility of methods for detecting generated outputs – including texts, images, codes, maps and more – are vital for upholding academic integrity. It can be argued that the ability to readily detect and distinguish AI-generated outputs from those produced through standard academic rigour by students is of paramount importance in mitigating the threats associated with the integration of GenAI in higher education.

To develop an effective framework and policy for integrating GenAI technology in higher education, the role of academics is crucial. Their perceptions of usage, knowledge, willingness to adopt and learn and the potential impacts of these new tools on their academic practices are vital for leveraging this technological advancement. Understanding academics' attitudes towards this evolving technology, their ability to detect student usage and its effects on their teaching methods is essential for the successful integration of GenAI in higher education (Law, 2024; Lawrence & Tar, 2018; Okoye et al., 2023; Timotheou et al., 2023). Insights into these dynamics will enable institutions to allocate resources more effectively. For instance, if a weak correlation is found between academics' knowledge of GenAI and their willingness to engage with it, this would justify increased investment in AI-focused professional development; conversely, a strong correlation might indicate that current resources are sufficient.

Methodology

Figure 1 illustrates the research methodology adopted in this study, outlining the procedural steps involved in data collection and analysis. It provides a visual representation of the process, leading up to the establishment and discussion of the results.

The study adopts a mixed-method research approach consisting of both quantitative and qualitative research methods. This approach enables a comprehensive and thorough analysis by integrating both quantitative and qualitative data to draw inferences and conclusions (Creswell, 2024).

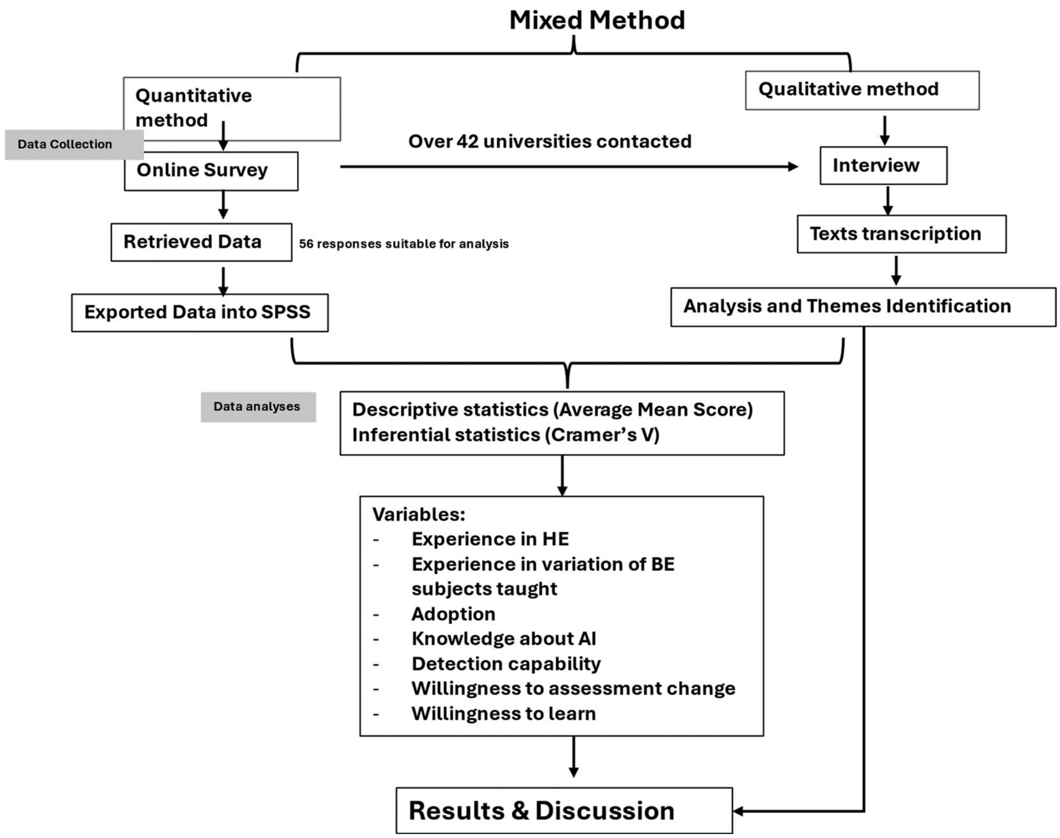

Figure 1. Data Collection Procedure. *Source:* Authors (2024).

For the quantitative approach, a questionnaire survey was designed and administered to the respondents *via* email, with addresses obtained through a web-scraping technique. The purposive sampling method adopted allows the study to target only built environment academics in the UK who are willing to participate. A total of 432 email addresses from built environment academics across 42 UK universities were collected, and the survey questionnaire was sent out (after obtaining the necessary ethical approval before data collection). However, only 56 responses were received in a format suitable for quantitative data analysis. Ethical approval for this study was obtained and participants' confidentiality and anonymity were strictly maintained throughout the study and reporting.

The survey questions were divided into three broad sections that enquire about:

i. academics' demographic characteristics (including, age, experience and subjects taught among others),
ii. impacts of GenAI on academic practice (including, readiness to change assessments, willingness to learn about GenAI and ease of detecting students' usage of GenAI among others) and
iii. academics' perceptions on the challenges, risks and benefits of GenAI to various elements of their academic practice.

Meanwhile, the qualitative research was undertaken through pre-arranged video interviews with six (6) respondents. These were the online survey participants who had indicated their interest in a follow-up interview. The interviews were conducted to further understand the academics' perceptions of the influence of GenAI technology on their academic practice and how they were managing the situation.

Data and analysis techniques

Quantitative data was generated from the survey and analysed using appropriate statistical techniques. In contrast, all data obtained from the interviews were transcribed, thematically analysed and discussed in relation to the key variables identified in the study.

The statistical techniques adopted in this study are both descriptive and inferential statistics. Where appropriate, frequency distribution, percentages, standard deviation and average mean scores (AMS) were adopted as descriptive statistics to present results from the survey. The frequencies are presented in tables alongside their respective percentages, which show the proportions in each variable category. AMS was also applied as a measure of central tendency that represents the sum of all values divided by the number of observations in a dataset (Baffoe-Djan & Smith, 2019; Fisher & Marshall, 2009). It provides a general indicator of the overall perception or opinion of the research participants regarding a specific question (Crew & Crew, 2020). The descriptive statistics together summarise the dataset and indicate the collective views or opinions of the respondents (Fisher & Marshall, 2009; Marshall & Jonker, 2010).

On the other hand, Cramer's V was applied as an inferential statistic to analyse the association between relevant variables. This statistic is derived from the Chi-square test and measures the strength of association between two categorical variables. Its value ranges from 0 (indicating no association) to 1 (indicating perfect association) (Wooditch et al., 2021). The technique is particularly useful for quantifying the strength of non-parametric relationships between variables being investigated (Wooditch et al., 2021). Table 1 presents the description of all the variables analysed using Cramer's V. Cramer's V and the descriptive statistics discussed above were conducted using SPSS.

Results and discussion

Demographics of respondents

Table 2 presents the demographic profile of the research participants. It delineates key demographic information, including academic experience, age, gender and the areas of specialisation of the respondents.

The table reveals a commendable distribution of respondents with over two years of experience, specifically: 2–5 years (21%), 5–10 years (20%), 10–20 years (29%) and over 20 years, comprising approximately 27% of the surveyed population. Similarly, participants in the interviews had more than ten years of teaching experience, while those with less than two years constituted only about 4%. Notably, 67% of the interviewees have more than 10 years of experience. The emphasis on the years of experience among respondents highlights that the results originate from highly experienced academics.

Table 1. Variable description.

Variable Description		Variable type	Likert scale categories
Experience_1	Experience in learning and teaching.	Categorical	1 = less than 2 years 2 = 2–5 years 3 = 5–10 years 4 = 10–20 years 5= above 20 years
Experience_2	Variation of subject taught	Binary	1 = 1 subject 2 = 2 subjects 3 = 3 subjects 4= > 3 subjects
Knowledge	Knowledge of Gen AI by academics	Categorical	1 = Minimal 2 = Good 3= Very good
Adoption	Adoption of Gen AI by academic	Binary	1 = Yes 0 = No
Detection	Perception of built environment academics on easy it is to detect students use of Gen AI	Categorical	1 = Extremely not easy 2 = Somewhat not easy 3= Neutral 4 = Somewhat easy 5 = Extremely easy
Assessment change	Academics changing assessment because of GenAI	binary	1= Changes made/plans to make changes 0 = No changes made and no plans to make changes
Willingness to learn	Academics' willingness to learn new skills to meet the need posed by GenAI	binary	1 = Yes 0 = No or maybe

Source: Authors (2024).

Table 2. Demographics of respondents.

Criterion	Description	Survey frequency (%)	Interview frequency (%)
Academic experience	Less than 2 years	2 (4)	–
	2–5 years	12 (21)	–
	5–10 years	11(20)	2 (33.3)
	10–20 years	16 (29)	3 (50)
	Above 20 years	15 (27)	1 (16.7)
Age	Less than 30 years	1 (2)	–
	31–40 years	19 (34)	1 (16.7)
	41–50 years	12 (21)	4 (66.7)
	Above 50 years	24 (43)	1 (16.7)
Gender	Male	34 (61)	4 (66.7)
	Female	20 (36)	2 (33.3)
	Not stated	2 (4)	–
Specialisation	Real estate	14 (25)	2 (33.3)
	Quantity surveying	5 (9)	–
	Planning	3 (5.2)	1 (16.7)
	Building surveying	4 (7)	
	Construction Management	10 (18)	1 (16.7)
	Others	32 (57)	1 (16.7)

Source: Authors (2024).

The age distribution reflects a comparable trend, with the lowest proportion being about 2% of the total respondent population in the survey. Participants aged over 50 represent the largest cohort at 43%, while those in the age ranges of 31–40 years and 41–50 years follow closely at 34% and 21%, respectively. The modal age of interview participants is between 41 and 50 years, accounting for 66.7%. Furthermore, the distribution indicates a predominance of male respondents, who make up over 60%, while female respondents account for less than 40% in both the survey and interviews.

Additionally, the core areas of specialisation among respondents during both stages of data collection are diverse, encompassing real estate, planning, construction management and other built environment disciplines, as illustrated in Table 1. The primary interpretation of the demographic data suggests a diverse mix of respondents with substantial academic experience.

Frequency distribution of survey responses

Table 3 presents a descriptive frequency table summarising respondents' views from the survey. It specifically shows the distribution of the analysed variables including academics' knowledge of GenAI, their ability to detect GenAI usage by students, the extent of GenAI adoption by academics, perceived increases in student use of GenAI, willingness to modify assessments due to GenAI, openness to learning about GenAI and the variation in subjects taught within the built environment discipline.

Table 3 delineates variations in the depth of understanding, implementation and possible impacts of GenAI among academics. While 46% of participants reported a 'good' level of comprehension, a notable 41% acknowledged possessing only a 'minimal' grasp of the subject. This disparity in understanding underscores the rapid pace of GenAI advancements and the challenges academics face in keeping abreast of technological developments. As Selwyn (2013, 2019) and Zhang et al. (2025) asserted, a lack of awareness among academics regarding emerging technologies can significantly impede their effective integration into pedagogical practice. Furthermore, only 32% of participants actively incorporated GenAI into their teaching methods. This relatively low adoption rate may be attributed to several factors, including insufficient institutional support, concerns over academic integrity or uncertainty regarding the efficacy of the technology. Lawrence and Tar (2018) similarly identified obstacles to the adoption of educational technology, emphasising the importance of institutional backing and opportunities for professional development.

Moreover, the data in Table 3 reveals that 66% of respondents observed an increase in AI-generated content in student assessments. This finding aligns with broader trends in higher education, where students are increasingly turning to AI platforms for academic support (Okoye et al., 2023; Zawacki-Richter et al., 2019). However, detecting such material remains a significant challenge, with only 5% of respondents finding it 'Extremely Easy,' while 37% considered it 'Somewhat Not Easy.' This issue underscores the urgent need for more sophisticated detection technologies and updated assessment frameworks to

Table 3. Frequency distribution and percentage of respondents' views on variables.

Criterion	Description	Frequency	Percentage (%)
Knowledge about AI	Minimal	23	41.1
	Good	26	46.4
	Very good	7	12.5
Detecting students use of Gen AI	Extremely not easy	2	3.6
	Somewhat not easy	21	37.5
	Neutral	12	21.4
	Somewhat easy	18	32.1
	Extremely easy	3	5.4
Adoption of Gen AI by academic	No	38	67.9
	Yes	18	32.1
Academics' perception of student use of Gen AI	No	19	33.9
	Yes	37	66.1
Assessment change	I do not intend to change	12	21.4
	I intend to change	28	50.0
	I've made changes	16	28.6
Willingness to learn	No	5	8.9
	Maybe	9	16.1
	Yes	42	75.0
Variation of subject taught	1 subject	49	87.5
	2 subjects	3	5.4
	3 subjects	3	5.4
	$>$ 3 subjects	1	1.8

Source: Authors (2024).

maintain academic integrity in the GenAI era. These concerns mirror the conclusions of Fischer et al. (2020), who noted that the potential for AI to generate plausible, yet inaccurate information presents substantial challenges for both academics and students alike.

Meanwhile, approximately 79% of respondents have either adopted or are willing to adapt their assessment methods in response to GenAI, highlighting the profound impact GenAI is already exerting or is expected to exert, on assessment practices in higher education, as posited by Okoye et al. (2023). In contrast, 75% of respondents expressed a willingness to further explore GenAI to enhance learning and teaching. However, 16% of respondents were uncertain about their readiness and willingness to engage with the technology in support of their academic roles, while approximately 9% were unwilling to do so. Additionally, the findings indicate that nearly 88% of respondents are specialist tutors, teaching within the domains of real estate, quantity surveying, building surveying, construction management and planning.

Perceptions on the challenges, risks and benefits of GenAI to academic practice

Table 4 presents respondents' perspectives on the potential challenges, risks and benefits of GenAI technology integration in learning and teaching. Academics' perceptions have been categorised and ranked as Strongly Agree (SA), Agree (A), Disagree (D), Strongly Disagree (SD) and Indifferent (I). The table displays the average ratings of respondents, represented by the mean, along with the standard deviation to indicate the level of variation in responses.

The results reveal that the most significant threat posed by GenAI technology lies in its potential for misuse. Table 4 indicates that the most agreed statement among respondents is that reliance on GenAI can facilitate plagiarism as the statement recorded the highest mean and the lowest standard deviation. In other words, the greatest concern among built environment academics is the risk of plagiarism facilitated by over-reliance on GenAI. This outcome is not surprising and aligns with existing outcomes from research impact of GenAI on the future of higher education (Asamoah et al., 2024; Jafari & Keykha, 2024; Yusuf et al., 2024). Similarly, the responses from the interviews conducted in this study suggest that interviewees view GenAI tools as addictive and potentially detrimental to the quality of learning if not properly used. Respondent 3 stated, '*My experience with ChatGPT is that I tend to double-check every little thing I do with it… I am concerned that when my students become aware of the tool, there is a high chance they will rely on it for their assessment tasks, which could encourage cheating.*'

Table 4. Potential impacts and concern with GenAI integration.

Proposition	Mean score	Std. deviation
Reliance on GenAI can facilitate plagiarism	3.30	0.913
GenAI can facilitate erosion of critical and independent thinking in higher education	3.04	1.159
GenAI can reduced students' engagements and interactions	2.61	1.186
GenAI can lead to job displacement and loss of human educators	1.86	1.257
GenAI can lead to perpetuation of biases and ethical dilemmas in educational contexts	2.16	1.616
GenAI can lead to loss of unique learning and teaching styles	2.21	1.436
GenAI can lead to depersonalisation of the learning experience	2.41	1.411
GenAI can be used as personalised assistance and 24/7 support for students	2.23	1.412
GenAI can mitigate language barriers to enhance inclusivity among students	2.63	1.329
GenAI can improve accessibility to learning materials	2.45	1.426
GenAI can be adopted as tools for evaluating written drafts before summative assessment	2.71	1.275
GenAI can provide an alternative to research and literature search tools	2.14	1.313
GenAI can support academics to access best practices for learning design and curriculum development	2.14	1.507
GenAI can offers an opportunity for lifelong learning among academics	2.02	1.555
GenAI can serve as a tool for brainstorming and generating ideas for group discussions	2.61	1.317
GenAI can be adopted as a tool for proofreading written pieces	2.21	1.592

Source: Authors (2024).

This aligns with the response from Respondent 4, who stated, '*I don't believe I need an AI tool to support my academic practice … and I don't want my students to cheat with it.*'

Additionally, the erosion of critical and independent thinking, along with reduced student engagement and interaction, are key challenges that respondents have identified as particularly concerning. This aligns with the concerns raised by Williams (2019) regarding the possibility of technology hindering rather than enhancing deep learning processes if not used thoughtfully.

Conversely, academics surveyed and interviewed do not perceive 'job displacement and the loss of human academics' as a significant threat. Table 4 shows that job displacement has the lowest mean score, indicating that it is not a major concern among built environment academics. As stated by Respondent 1, '*… I feel less threatened that AI will replace me in my role as an academic … Will GenAI be able to take students on a site visit?*'

Several participants expressed apprehensions regarding the ethical application of GenAI, namely on the protection of data privacy and the possibility of discriminatory effects. These concerns are consistent with wider debates in the field on the ethical consequences of AI in education (Zawacki-Richter et al., 2019). The other concerning factors may be the loss of unique learning and teaching styles along with the depersonalisation of the learning experience. These concerns are consistent with the findings of Timotheou et al. (2023) and Chiu et al. (2023) that the adoption and over-reliance of GenAI could hinder the longstanding educational processes.

On the contrary, some benefits of using AI were also addressed. According to the participants, the most important benefits for academics are, that it can be used as a tool for evaluating written drafts before summative assessment and a tool for brainstorming and generating ideas for group discussions. Academics work long hours in academia undertaking assessments (Mikeladze et al., 2024) and AI tools can potentially help reduce the time academics spend on assessments by providing effective feedback and personalised teaching as well as for brainstorming.

To gain further insight into the interrelationship between the descriptive variables, the study investigated the relationships between the investigated variables, as presented in Table 5.

Table 5 elucidates the interrelationships between various aspects of academics' perspectives on the integration of GenAI within teaching and learning across built environment disciplines. Specifically, it underscores the correlations between academics' experience, knowledge, adoption of GenAI, their capacity to discern students' utilisation of GenAI, their inclination towards further learning, their perceptions of student engagement with GenAI and their overall willingness to embrace this technology.

Table 5 shows that academics with greater knowledge of AI have a higher capability to detect its use by students ($r = 0.259$), adopt it into their teaching practices ($r = 0.407$, $^{***}p < 0.001$) and perceive changes in students' use of AI ($r = 0.285$, $^{*}p < 0.05$). This suggests that AI knowledge acts as a crucial foundation for effective engagement with the technology, influencing how academics integrate GenAI into their pedagogical practices.

Table 5. Cramer's V values.

	Knowledge	Detection	Adoption	Perception	Assessment change	Willingness to learn	Variation	Experience
Knowledge	1	0.259	0.407***	0.285*	0.208	0.180	0.217	0.213
Detection		1	0.357	0.328	0.306	0.332*	0.224	0.322*
Adoption			1	0.332***	0.328**	0.133	0.404**	0.214
Perception				1	0.306*	0.040	0.199	0.290
Assessment change					1	0.242	0.324*	0.355*
Willingness to learn						1	0.333*	0.235
Variation							1	0.168
Experience								1

***Sig at 0.01, **Sig at 0.05 and *Sig at 0.1.
Source: Authors (2024).

The results show that academics with more experience are better at detecting AI use by students ($r = 0.322$, $^{*}p < 0.05$), which in turn correlates with their willingness to adapt assessments in response to GenAI ($r = 0.306$, $^{*}p < 0.05$). This highlights that experienced academics, who are adept at identifying AI use, are more proactive in modifying their assessment strategies. These suggest that AI detection is not merely a technical skill but also intertwined with broader pedagogical awareness and experience. The correlation between GenAI adoption and willingness to change assessments is also significant ($r = 0.328$, $^{**}p < 0.01$). Academics who adopt GenAI are more likely to view it as a transformative force in education, encouraging them to revise their assessment methods to align with the challenges and opportunities posed by the technology. Furthermore, the adoption of GenAI by academics correlates with their perception of students' AI use ($r = 0.332$, $^{***}p < 0.001$), reinforcing the idea that academics' perceptions of student engagement with AI shape their own pedagogical decisions.

Moreover, academics' willingness to learn about GenAI is strongly associated with their ability to detect AI use by students. This suggests that those open to continuous learning are better positioned to recognise AI's presence in student work, thus demonstrating the reciprocal relationship between knowledge acquisition and practical application.

Interestingly, academics teaching across multiple built environment subjects are more inclined to adopt GenAI and adjust their assessments than those teaching a single subject. This flexibility could be attributed to their exposure to varied teaching approaches, making them more adaptable to new technologies.

Finally, the study highlights the relationship between academics' perception of students' use of GenAI and their propensity to alter assessment methods ($r = 0.306$, $^{*}p < 0.05$). As academics become more aware of the increasing use of AI by students, they are more likely to modify assessments to address issues, such as plagiarism or superficial learning. This indicates that as AI becomes more pervasive in student practices, academics will need to continuously evolve their teaching and assessment strategies to maintain academic integrity.

Conclusions

This study investigates the impact of GenAI technology on teaching and learning in the built environment discipline, focusing on the perspectives of academics. By exploring the relationships between academics' experience, knowledge of AI, their willingness to adopt AI technologies and their ability to detect student use of AI, the research provides valuable insights into the integration of these technologies in higher education. Employing a mixed-methods approach, the study combined qualitative interviews with quantitative surveys to gather comprehensive data from built environment academics.

The findings of this study underscore the central role of academics' knowledge, experience and teaching scope in the successful integration of GenAI technology in higher education, particularly within the built environment disciplines. While GenAI offers numerous benefits – such as enhanced inclusivity, accessibility and assessment efficiency – academics also express concerns regarding its potential misuse, including academic dishonesty, the dilution of critical thinking and the depersonalisation of learning experiences. Experienced academics, particularly those teaching across multiple disciplines, are more inclined to embrace GenAI and adapt their assessment methods to address these challenges.

These insights point to the necessity for a structured and comprehensive regulatory framework. Such a framework should balance the opportunities presented by GenAI with the need to preserve the integrity of education. It must include ethical guidelines addressing AI's challenges, such as bias, academic integrity and fairness, particularly in the context of multidimensional disciplines like the built environment. Furthermore, institutions must prioritise professional development programmes that enhance AI literacy among academics, equipping them with the skills to detect AI-generated content and integrate AI responsibly in teaching and assessment.

Moving forward, the establishment of a flexible, scalable and standardised regulatory framework is crucial. This framework should ensure that the adoption of GenAI aligns with both academic rigour and ethical principles, supporting innovation while safeguarding the quality and equity of education. The results obtained from this research on the associations between specific academic characteristics, perceptions of GenAI technology, and its impacts on academics' teaching and learning practices should be reasonably considered in the development of regulatory frameworks for the integration of GenAI technology in the built environment disciplines and broader higher education.

While this study offers valuable insights into the influence of GenAI on teaching and learning within the built environment discipline, several limitations should be acknowledged in adopting or implementing its findings. First, the study relied on an online survey, which may have introduced response bias, as the sample may not fully represent the broader academic community. Furthermore, with only 56 survey participants, the sample size is relatively small, limiting the generalisability of the findings to all academics within the field. Similarly, the research participants are from the field of built environment education, and their perspectives may differ significantly from those in other disciplines. The analysis was predominantly descriptive, which, while useful for summarising trends, does not allow for in-depth causal inferences or deeper exploration of complex relationships. These limitations suggest that future research with a larger, more diverse sample and more advanced analytical techniques could provide further insights into the effects of GenAI in higher education.

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