Understanding Academic Staff Attitudes Toward GenAI in Teaching

Clara Hope Rispler,
Michal Mashiach-Eizenberg, Gila Yakov

The Max Stern Yezreel Valley College

First published on June 2025

Keywords

Generative AI, Higher Education, faculty attitudes, TPACK, Personal Innovativeness in IT, Perceived Usefulness, TAM

Abstract

This study examines the attitudes of academic staff toward the use of generative artificial intelligence (GenAI) in higher education teaching. Focusing on faculty members at a college in Israel, the study explores how attitudes are associated with self-reported levels of technological pedagogical content knowledge (TPACK) self-efficacy, personal innovativeness in IT (PIIT), and two perceptual constructs drawn from the Technology Acceptance Model (TAM): perceived usefulness and perceived ease of use. A cross-sectional survey design was used, with data collected from 84 lecturers. Correlation and hierarchical regression analyses revealed that both PIIT and TPACK self-efficacy were positively associated with attitudes toward GenAI, with perceived usefulness and ease of use emerging as significant mediators. Specifically, the effect of TPACK self-efficacy on attitudes was fully mediated by these perceptual variables, while PIIT retained a significant direct effect. The findings suggest that faculty attitudes toward GenAI are shaped by both individual dispositions and evaluative judgments about the tool's pedagogical relevance and usability. This research contributes to the growing literature on AI in education by providing empirical evidence on the attitudinal antecedents relevant to faculty engagement and may inform institutional strategies that support the thoughtful and differentiated integration of GenAI in teaching.

Corresponding Author: Clara Hope Rispler, The Max Stern Yezreel Valley College. Email: clarar@yvc.ac.il. To quote this article: Rispler et al., 2025. "Understanding Academic Staff Attitudes Toward GenAI in Teaching" *Journal of Ethics in Higher Education* 6.1 (2025): 209–235. DOI: 10.26034/fr.jehe.2025.8397

Introduction

The emergence of generative artificial intelligence (GenAI) presents higher education institutions with both opportunities and challenges. Tools such as ChatGPT and other large language models have introduced new modes of content creation, reshaping student engagement, assessment practices, and pedagogical frameworks (Pavlik, 2023; Linden et al., 2025). As these technologies gain traction, universities are increasingly expected to develop coherent and ethically grounded responses that address instructional, institutional, and policy dimensions (An et al., 2025; Wang et al., 2024).

Given their role in designing learning environments, setting academic standards, and responding to evolving institutional expectations, faculty members are central to understanding and implementing generative AI in higher education (Baig & Yadegaridehkordi, 2025; Linden et al., 2025). Studies increasingly highlight that teaching staff are not only end-users but also agents of curricular and ethical adaptation, influencing the direction of institutional policies and the development of responsible integration strategies (An et al., 2025; Wang et al., 2024). Understanding faculty perceptions —regarding usefulness, risks, and professional values—is therefore essential for developing GenAI responses that are pedagogically effective and contextually informed (Barakat, 2024; Sandra et al., 2024).

This study examines the perceptions of academic staff in an Israeli higher education institution regarding generative AI, with a focus on patterns of use, ethical considerations, and the perceived pedagogical relevance of this technology. Grounded in recent calls for more inclusive investigations of GenAI integration across stakeholder groups (Linden et al., 2025), the research aims to contribute to a broader understanding of how higher education can respond not only as adopters of innovation but as agents of pedagogical and ethical leadership in an evolving technological landscape.

1. Literature Review

The integration of artificial intelligence (AI) into higher education has shifted from speculative discourse to a tangible reality, raising complex questions for educators, institutions, and policy-makers alike (Chan, 2023). Among recent developments, generative AI (GenAI)—a class of AI technologies capable of producing original content such as text, images, or code based on large datasets (Baytak, 2023)—has gained prominence. One of the most widely used GenAI tools is ChatGPT, released in November 2022 by OpenAI (Lock, 2022; Bozkurt et al., 2023), followed by a rapid proliferation of similar applications supporting educational tasks (Chan & Hu, 2023). The emergence of such tools has accelerated the transformation of higher education by enabling new modes of content generation and student engagement, while also provoking concerns over authorship, academic integrity, and the validity of learning outcomes (Sudan et al., 2024). Although institutional responses remain uneven, scholars increasingly emphasize the need for strategic frameworks that promote both pedagogical innovation and ethical governance (Selvaratnam & Venaruzzo, 2024). GenAI integration is not merely a technical or logistical matter—it intersects with more profound questions about epistemology, faculty agency, and the evolving mission of universities as ethical leaders in digital society (Khanfir, 2024). In this context, the attitudes, competencies, and preparedness of academic staff have emerged as critical mediators of how GenAI is interpreted, adopted, and regulated at the institutional level (Shankar, 2024). This literature review is organised around four key domains that emerge from current research: pedagogical implications, ethical considerations, assessment and institutional responses, and faculty readiness. Each of these areas will be examined in turn to contextualize the integration of GenAI in higher education from the perspective of academic staff.

Pedagogical Implications of Generative AI

The adoption of AI in academic instruction has compelled educators to reconsider long-standing pedagogical models and instructional practices. Rather than functioning as a supplementary tool, generative AI has begun to reshape the conditions of knowledge construction, prompting a shift from content transmission to skills in evaluation, curation, and critical synthesis (Lindsay & Jacka, 2024). Instructors are increasingly expected to integrate AI literacy into the learning experience, often without sufficient training or institutional support (Linden et al.,2025; Southworth et al., 2023). This gap between technological advancement and pedagogical infrastructure has led to inconsistencies in implementation and exacerbated existing inequalities in access to innovation (Elyakim, 2025). Moreover, faculty members report varying degrees of comfort and competence in designing learning activities that align with ethical use of AI, revealing a tension between innovation and professional identity (Sudan et al., 2024). These findings point to the need for comprehensive faculty development initiatives that equip instructors not only with technical skills but also with pedagogical frameworks tailored to AI-mediated environments (Shankar, 2024).

Ethical Considerations and Academic Integrity

The rise of generative AI has brought renewed urgency to discussions surrounding academic integrity, particularly as students gain unprecedented access to automated content creation tools. Concerns have been raised about the erosion of traditional authorship, with scholars noting that institutional honour codes and plagiarism policies often lag technological capabilities (Choung et al., 2023). Recent findings suggest that ethical concerns, including transparency and fairness, also shape faculty satisfaction and the continued use of GenAI technologies (Baig & Yadegaridehkordi, 2025). Ethical tensions also extend to faculty use of AI, as instructors experiment with tools for grading, feedback, or lecture preparation, frequently without formal guidance on acceptable practices (Selvaratnam & Venaruzzo, 2024). This ambiguity has prompted calls for human-centered frameworks that balance innovation with institutional values, emphasising accountability, transparency, and the cultivation of trust (Class & de la Higuera, 2024). Still, the lack of enforceable regulatory mechanisms remains a challenge, particularly in cross-cultural and global educational contexts where norms around AI use vary considerably (Khanfir, 2024). Ultimately, safeguarding ethical standards in AI-enhanced learning requires not only policy development but active dialogue among educators, administrators, and students (Lindsay & Jacka, 2024).

Assessment Design and Institutional Adaptation

As generative AI disrupts traditional modes of assessment, educators are increasingly compelled to rethink how student learning is measured and validated. Conventional assignments such as essays and reports are particularly susceptible to automation, prompting renewed interest in authentic assessment models that emphasize process, reflection, and creativity over replication (Sudan et al., 2024). Institutions that have begun adapting to this shift often promote formative approaches that require students to disclose, justify, or critically engage with their use of AI tools, thereby reframing the role of technology as a catalyst for higher-order thinking rather than a shortcut (Shankar, 2024). This pedagogical redirection is reflected in emerging frameworks, such as the AAA model, which categorizes instructional responses to AI into three categories—Avoid, Acknowledge, and Act—based on the nature of the learning task and intended outcomes (Lindsay & Jacka, 2024). The model provides educators with a structured approach to determine when to exclude, integrate, or strategically leverage AI in teaching. Nonetheless, implementation remains uneven, and many educators report uncertainty regarding how to balance academic standards with technological realities (Khong, 2023). Recent policy reviews reveal that while many universities have issued guidelines endorsing GenAI in the classroom, they often do so without offering sufficient ethical or pedagogical infrastructure, thereby placing a disproportionate burden on instructors to interpret, implement, and manage its use (McDonald et al., 2025). This trend intensifies existing tensions surrounding the validity of assessments, academic authorship, and professional responsibility. Without coherent institutional policies and professional development tailored to AI-informed assessment, adaptation efforts risk remaining fragmented and inconsistently applied (Southworth et al., 2023).

Faculty Readiness, Identity, and Institutional Leadership

Faculty attitudes and readiness play a pivotal role in shaping the trajectory of AI adoption in higher education, influencing not only pedagogical uptake but also the ethical climate in which these tools are used. Empirical studies consistently highlight wide variation in instructors' perceptions of generative AI, ranging from enthusiastic engagement to ambivalence or resistance, often linked to differences in self-efficacy and disciplinary culture (Howard et al., 2021). Instructors with higher technological pedagogical content knowledge (TPACK) tend to feel more confident when integrating novel technologies, which correlates with openness toward digital innovation (Archambault & Crippen, 2009). Accordingly, it is expected that faculty members with higher levels of TPACK self-efficacy will report more positive attitudes toward the use of GenAI in teaching.

Another relevant dimension is personal innovativeness in information technology, which reflects an individual's willingness to experiment with and adopt new digital tools. Previous work suggests that more innovative instructors are quicker to recognise the pedagogical potential of GenAI and to incorporate it into their instructional repertoire (Deng, 2023; Khong, 2023).

Intermediary factors also shape these relationships. The Technology Acceptance Model (TAM) posits that perceived usefulness and perceived ease of use significantly mediate the relationship between technological beliefs and attitudes and behaviors (Chan, 2023). In this context, faculty members with strong TPACK profiles may be more likely to perceive GenAI tools as usable and pedagogically relevant, which in turn fosters more favourable attitudes toward these tools. As such, perceived usefulness and perceived ease of use are expected to mediate the relationship between TPACK self-efficacy and attitudes toward GenAI.

Despite a growing body of research on the integration of generative AI in higher education, substantial gaps remain in understanding how academic staff perceive and engage with these technologies in practice (Chan, 2023; Selvaratnam & Venaruzzo, 2024; Korcz et al., 2023). Recent studies explore faculty perspectives directly, including their concerns about workload, preparedness, and pedagogical alignment with GenAI tools (Baig &

Yadegaridehkordi, 2025; Linden et al., 2025). Moreover, while conceptual models have been proposed to guide the adoption of ethical AI, further studies are needed to examine how these abstract frameworks align with the lived realities of educators navigating their day-to-day teaching responsibilities (Deng, 2023; Lindsay & Jacka, 2024). While faculty may express openness toward GenAI integration, they often lack institutional guidance or structured pathways for implementation (Shankar et al., 2024).

The present study examines academic staff attitudes toward the use of generative AI in teaching, with a focus on how these attitudes relate to self-efficacy in technology integration, openness to innovation, and perceptions of usefulness and ease of use. By situating this investigation within the context of a single college, the study offers a grounded perspective on how faculty interpret and evaluate GenAI at the instructional level. In doing so, it contributes to a more nuanced understanding of how individual and perceptual factors intersect with broader technological change in the post-ChatGPT era. To examine these relationships empirically, the study tested six hypotheses addressing the associations between TPACK self-efficacy, personal innovativeness in IT, perceived usefulness, perceived ease of use, and attitudes toward GenAI in teaching:

A positive relationship is expected between TPACK self-efficacy and attitudes toward the use of GenAI in teaching.

A positive relationship is expected between personal innovativeness in IT and attitudes toward the use of GenAI in teaching.

A positive relationship is expected between perceived usefulness and attitudes toward the use of GenAI in teaching.

There will be a positive relationship between perceived ease of use and attitudes toward the use of GenAI in teaching.

Perceived usefulness and perceived ease of use will mediate the relationship between TPACK self-efficacy and attitudes toward GenAI in teaching.

Perceived usefulness and perceived ease of use will mediate the relationship between personal innovativeness in IT and attitudes toward GenAI in teaching.

2. Method

1. Participants and data collection

The current study analysed data obtained from a cross-sectional online survey conducted among lecturers teaching at a college in northern Israel between April 24 and May 24, 2024. The questionnaire was emailed to all lecturers who teach at the college. One hundred and ten lecturers responded to the questionnaire, while twenty-six respondents were excluded because their questionnaires were incomplete. Therefore, the data analysis included eighty-four lecturers who completed the questionnaire in full.

The college ethics committee approved the research protocol (Ethics Number: [disclosed name] 2024-68). After receiving relevant information and a brief explanation of the study's general purpose, content, procedure, and confidentiality, all participants agreed to participate voluntarily. The participants were told the survey data would be used solely for research purposes and that they could withdraw from participation at any time.

The questionnaire was constructed based on several validated English-language questionnaires (Al-Adwan et al., 2023; Howard et al., 2021; Stockless, 2018; and Khong et al., 2023). We made slight adjustments by changing the type of technology described in the questionnaire to GenAI. The questionnaire was translated into Hebrew and then back-translated into English to evaluate accuracy (Brislin, 1980).

2. Measures

Demographics questionnaire - The participants were asked to provide their age, gender, education, academic status, academic rank, teaching experience (in years), and the departments in which they teach.

Personal Innovativeness in IT (PIIT) was assessed using a four-item questionnaire developed by Al-Adwan et al. (2023), which evaluates lecturers' willingness to explore, adopt, and utilise new technologies. The instrument includes three positively worded items—for example, "If I heard about a new information technology, I would look for ways to experiment with it"—and one negatively worded item: "In general, I am hesitant to try out new information technologies." Responses were rated on a five-point Likert scale ranging from 1 (strongly disagree) to 5 (strongly agree). A composite mean score was calculated for the PIIT scale after reversing the negative item, with higher scores indicating greater personal innovativeness in IT. The internal consistency reliability (Cronbach's alpha) was reported as α=0.918 in Al-Adwan et al. (2023) and α=0.845 in the current study.

TPACK self-efficacy - Technological Pedagogical and Content Knowledge (TPACK) self-efficacy was measured using the questionnaire developed by Howard et al. (2021), which assesses the pedagogical and content-related dimensions of online teaching readiness. An example item is: "My ability to implement district curriculum in an online environment." Responses were recorded on a five-point Likert scale ranging from 1 (strongly disagree) to 5 (strongly agree). A composite mean score was calculated for the TPACK self-efficacy scale, with higher scores indicating greater confidence in lecturers' ability to effectively integrate technology into their pedagogical and content practices in online settings. The internal consistency reliability (Cronbach's alpha) was α=0.93 in Howard et al. (2021) and α=0.952 in the present study.

Perceived Usefulness - Perceived usefulness (PU) was measured using Stockless' (2018) six-item questionnaire, which tests the degree to which lecturers believe utilising GenAI will enhance their teaching ability in academia. An example item is "Generative Artificial Intelligence can be useful for improving my work as a lecturer". The degree of agreement on each item is measured on a Likert scale, ranging from 1 (strongly disagree) to 5 (strongly agree). For data processing, one mean was calculated for the perceived usefulness scale, and a high score indicates that lecturers perceive GenAI as more useful for their teaching. The internal reliability (Cronbach's alpha) in the study of Stockless (2018) was α=0.95, and in our study it was α=0.923.

Perceived Ease of Use - To measure the perceived ease of use (PEU), we used the Stockless (2018) six-item questionnaire, which tests the degree to which lecturers' expectations of the system's ease of use. An example item is "It is easy for me to learn to use creative artificial intelligence". The degree of agreement on each item is measured on a Likert scale between 1 = strongly disagree and 5 = strongly agree. For data processing, the mean was calculated for the perceived ease of use scale, and a high score indicates that lecturers perceive GenAI as easier to meet their teaching needs. The internal reliability (Cronbach's alpha) in the study of Stockless (2018) was $\alpha=0.95$, and in our study it was $\alpha=0.914$.

Attitude towards Use GenAI - Attitude towards use GenAI (AT) was measured using Khong et al. (2023) questionnaire, which tests an individual's positive or negative feelings toward using technology. The original questionnaire consists of four items, one reflecting a positive attitude: "I am comfortable teaching with generative artificial intelligence", and three reflecting negative attitudes, for example, "teaching with generative artificial intelligence is stressful". In light of recent findings suggesting that ethical concerns—e.g., around possible bias, the need for transparency, and potential misuse—significantly shape user attitudes toward GenAI in education (Al Zaidy, 2024; Barrientos et al., 2024; Mohamed, 2024; Morandín-Ahuerma, 2024), we added a fifth item addressing this dimension: "The use of generative artificial intelligence for teaching is accompanied by ethical problems". The degree of agreement on each item is measured on a Likert scale, ranging from 1 (strongly disagree) to 5 (strongly agree). For data processing, one mean was calculated for the Attitude towards use GenAI scale (after reversing the negative items), and a high value indicates that lecturers' attitudes towards the use of GenAI are more positive. The internal reliability (Cronbach's alpha) in the study by Khong et al. (2023) was $\alpha = 0.92$, and in our study (for the five items), it was $\alpha = 0.714$.

3. Data Analysis

Using IBM SPSS Statistics 28.0, analysis was conducted for 84 responses. Missing values were less than 0.7% and were not replaced. Cronbach's α coefficient was measured to verify the reliability of the measurement tools used in the study. First, descriptive analyses were conducted to describe the participants' demographic characteristics. Second, Pearson and Spearman Correlations were performed to explore the relationships between the demographic characteristics and the research variables. Pearson correlations were also performed to explore relationships between the research variables themselves. Next, a hierarchical regression analysis was conducted to test the contribution of all variables to predicting attitude towards the use of GenAI. Finally, we conducted an analysis using a multiple-mediation approach (Preacher & Hayes, 2008). This analysis ensured the unstandardised direct effects, as well as the unique indirect effects of each mediator, and the combined overall effect of the mediating variables. Two mediators (perceived usefulness and perceived ease of use) were entered into the model simultaneously. The multiple-mediation approach utilises a bootstrap test, for which we generated 5000 samples, to produce 95% confidence intervals which indicate a significant indirect effect if they do not include 0 (Hayes, 2017). Significance was set at the .05 level, and all tests of significance were two-tailed.

4. Results

Demographic characteristics

The study included 84 lecturers, 70 of whom were female (83%) and 14 were male (17%). Their ages ranged from 29 to 71, with an average age of 50.5 (SD = 9.0). Most of the lecturers have a Ph.D. (71.4%), and about half of them (52.4%) are Tenure-track faculty members. Approximately one-third of the lecturers (34.5%) are senior lecturers or associate professors. The average teaching experience is 13.5 years (SD = 7.5). The sample demographic and professional characteristics are reported in Table 1.

Table 1: Demographic and professional characteristics of the sample (N=84)

	N	%
Gender		
Female	70	83.3%
Male	14	16.7%
Education		
Master's degree	24	28.6%
Ph.D	60	71.4%
Academic status		
Tenure-track faculty member	44	52.4%
Adjunct lecturer	16	19.0%
Teaching fellow	24	28.6%
Academic rank[a]		
Teacher	7	8.3%
Senior Teacher	4	4.8%
Lecturer	35	41.7%
Senior Lecturer	27	32.1%
Associate Professor	2	2.4%
	Mean (SD)	
Age[b] (years)	50.5 (9.0)	
min-max	29-71	
Teaching experience (years)	13.5 (7.5)	
min-max	1-30	

Note. SD = standard deviation.

[a] Missing: 9 (10.7%).

[b] Missing: 5 (6.0%).

The relationship between the demographic characteristics and the research variables

Table 2 shows Pearson correlations for the relationship between age, teaching experience, and the research variables and Spearman correlations for the relationship between academic rank and the research variables.

Table 2: Pearson and Spearman Correlations between the demographic characteristics and the research variables

	Age	Teaching experience	Academic rank
Personal innovativeness in IT	-0.14	-0.24*	-0.01
TPACK self-efficacy	-0.37***	-0.25*	-0.19
Perceived usefulness	-0.25*	-0.22*	-0.06
Perceived ease of use	-0.37***	-0.28**	0.01
Attitude towards use	-0.19*	-0.36***	-0.04

* *p*<.05, ** *p*<.01, *** *p*<.001
Abbreviation: TPACK, Technological Pedagogical and Content Knowledge

Table 2 shows a significant negative correlation (small to medium effect size) between respondents' age and TPACK self-efficacy, perceived usefulness, perceived ease of use and attitude towards. No significant correlation was found between respondents' age and personal innovativeness in IT. There was also a significant negative correlation (small effect size) between teaching experience and personal innovativeness in IT, TPACK self-efficacy, perceived usefulness, perceived ease of use and attitude towards use of GenAI. In the context of academic rank, all correlations were found to have a weak effect and were not statistically significant.

Correlations between the research variables

Correlations between all the research variables were explored and are reported in Table 3.

Table 3: Pearson correlations, Cronbach's alpha, means and SDs of the research variables (N=84)

	1	2	3	4	Cronbach's alpha	*M*	*SD*
1. Personal innovativeness in IT	1				.845	3.42	0.95
2. TPACK self-efficacy	.59*	1			.952	3.65	0.83
3. Perceived usefulness	.58*	.62*	1		.923	3.58	0.79
4. Perceived ease of use	.59*	.66*	.56*	1	.914	3.08	0.86
5. Attitude towards use	.60*	.53*	.59*	.61*	.714	3.31	0.74

Note. M = Mean; *SD* = standard deviation; **p*<.001
Abbreviation: TPACK, Technological Pedagogical and Content Knowledge

As shown in Table 3, all correlations are positive and statistically significant. There was a significant positive correlation between personal innovativeness in IT and TPACK self-efficacy (r=.59), perceived usefulness (r=.58), perceived ease of use (r=.59), and attitude towards use (r=.60). In addition, there was a significant positive correlation between TPACK self-efficacy and perceived usefulness (r=.62), perceived ease of use (r=.66) and attitude towards use (r=.53). Finally, there was a significant positive correlation between perceived usefulness and perceived ease of use (r=.56), between perceived usefulness and attitude towards use (r=.59) and between perceived ease of use and attitude towards use (r=.61).

Hierarchical linear regression analysis for predicting attitude towards the use of GenAI

Hierarchical linear regression was used to predict attitude towards the use of GenAI. In the first step, teaching experience was entered into the regression model (no significant contribution was found for the rest of the demographic characteristics). In the second step, personal innovativeness in IT and TPACK self-efficacy were entered into the regression model. In the third step, perceived usefulness and perceived ease of use were entered into the regression model. The results of these analyses are presented in Table 4.

Table 4: Hierarchical regression analysis for predicting attitude towards the use of GenAI (N=84)

Predictor Variable	*B*	*S.E*	*β*	*t*	*p*	R^2
Step 1: (Constant)	3.79	.16		24.02	<.001	.13
Teaching experience	-.04	.01	-.36	-3.50	**<.001**	
Step 2: (Constant)	1.72	.35		4.94	<.001	.45
Teaching experience	-.02	.01	-.20	-2.34	**.022**	
Personal innovativeness in IT	.32	.08	.42	4.02	**<.001**	
TPACK self-efficacy	.21	.09	.23	2.23	**.028**	
Step 3: (Constant)	1.28	.35		3.65	<.001	.53
Teaching experience	-.02	.01	-.17	-2.05	**.044**	
Personal innovativeness in IT	.20	.08	.25	2.36	**.021**	
TPACK self-efficacy	-.01	.10	-.01	-0.06	.956	
Perceived usefulness	.24	.10	.26	2.44	**.017**	
Perceived ease of use	.24	.10	.28	2.49	**.015**	

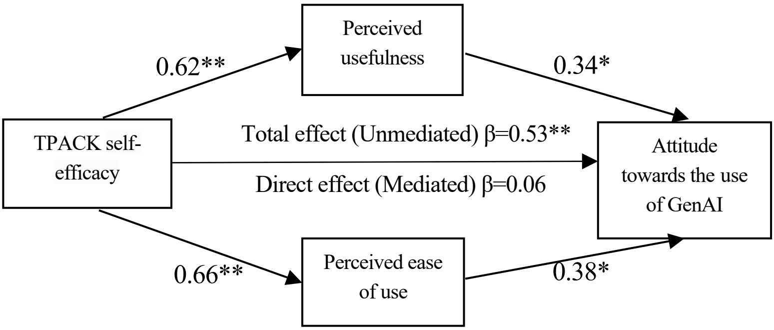
Note. B = Unstandard coefficient; *S.E* = Standard Error; *β* = Standard coefficient. Boldface font highlights a significant effect. Abbreviation: TPACK, Technological Pedagogical and Content Knowledge

In step one, teaching experience was a significant predictor of the attitude towards the use of GenAI. It was found that the longer lecturers have been teaching, the more negative their attitudes towards GenAI are. The teaching experience explained 13% of the variance in the attitude towards the use of GenAI. In step two, personal innovativeness in IT and TPACK self-efficacy were significant predictors of the attitude towards the use of GenAI. It was found that the more lecturers perceive themselves as innovative in IT and the higher their TPACK self-efficacy, the more positive their attitudes towards GenAI are. These variables accounted for an additional 32% of the explained variance. In step three, perceived usefulness and perceived ease of use were significant predictors of the attitude towards the use of GenAI. It was found that the more the lecturers perceive GenAI as more useful and easier to use, the more positive their attitudes towards GenAI are. These variables added 8% to the explained variance. In total, our model explained 53% of the variance of attitude towards the use of GenAI. Moreover, the model is statistically significant ($F(5,78)=17.63$, $p<.001$). Perceived usefulness and perceived ease of use as mediating between TPACK self-efficacy and attitude towards the use of GenAI.

Perceived usefulness and perceived ease of use as mediating between TPACK self-efficacy and attitude towards the use of GenAI

In the regression analysis presented in the previous section, it was found that in the second step the variable TPACK self-efficacy significantly predicts the attitudes, while in the third step, when the variables perceived usefulness and perceived ease of use were entered, the variable TPACK self-efficacy has no contribution at all to predicting the attitudes. This finding indicates mediation between TPACK self-efficacy and attitude towards the use of GenAI. To test the mediation models, we used the multiple mediation approach (Preacher & Hayes, 2008). Two mediators (perceived usefulness and perceived ease of use) were entered into the models simultaneously. The results of this analysis are presented in Figure 1.

Figure 1: A multiple mediation model of TPACK self-efficacy on attitude towards the use of GenAI through perceived usefulness and perceived ease of use. Standardized regression coefficients are provided along the paths.



*$p<.01$; **$p<.001$
Abbreviation: TPACK, Technological Pedagogical and Content Knowledge

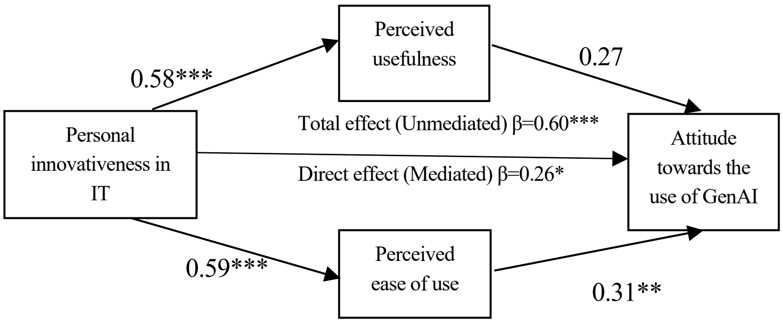
The multiple mediation analyses indicated a significant total effect (B=0.47, SE=0.08, β=0.53, p<0.001) between TPACK self-efficacy and attitude towards the use of GenAI. In addition, the direct effect was not significant (B=0.06, SE=0.11, β=0.06, p>0.05). The total indirect effect of the mediators was significant – mediation effect=0.41, CI=(0.25, 0.60). These results indicate that perceived usefulness and perceived ease of use fully mediate the relationship between TPACK self-efficacy and attitude towards the use of GenAI. An examination of specific indirect effects indicates that perceived usefulness and perceived ease of use are mediators of the relationship between TPACK self-efficacy and attitude towards the use of GenAI. Specifically, TPACK self-efficacy was positively related (β=0.62) to perceived usefulness, which, in turn, was positively related (β=0.34) to attitude. Additionally, TPACK self-efficacy was positively related (β=0.66) to perceived ease of use, which, in turn, was positively related (β=0.38) to attitude (see Figure 1).

Perceived usefulness and perceived ease of use as mediating between personal innovativeness in IT and attitude towards the use of GenAI

Another mediation model tested is that perceived usefulness and perceived ease of use will mediate the relationship between personal innovativeness in

IT and attitudes toward GenAI in teaching (Hypothesis 6). Two mediators (perceived usefulness and perceived ease of use) were entered into the models simultaneously. The results of this analysis are presented in Figure 2.

Figure 2: A multiple mediation model personal innovativeness in IT on attitude towards the use of GenAI through perceived usefulness and perceived ease of use. Standardized regression coefficients are provided along the paths.



* *p*<.05, ** *p*<.01, *** *p*<.001

The multiple mediation analyses indicated a significant total effect (B=0.47, SE=0.07, β=0.60, p<0.001), and direct effect (B=0.20, SE=0.08, β=0.26, p<.05), between personal innovativeness in IT and attitude towards the use of GenAI. The total indirect effect of the mediators was significant – mediation effect=0.26, CI=(0.15, 0.39). These results indicate that perceived usefulness and perceived ease of use partially mediate the relationship between personal innovativeness in IT and attitude towards the use of GenAI An examination of specific indirect effects indicates that perceived usefulness and perceived ease of use are mediators of the relationship between personal innovativeness in IT and attitude towards the use of GenAI. Specifically, personal innovativeness in IT was positively related (β=0.58) to perceived usefulness, which, in turn, was positively related (β=0.27) to attitude. Additionally, personal innovativeness in IT was positively related (β=0.59) to perceived ease of use, which, in turn, was positively related (β=0.31) to attitude (see Figure 2).

5. Discussion and Implications

This study investigated the attitudes of academic staff toward the use of generative AI in teaching. To do so, it focused on how these attitudes are associated with lecturers' self-efficacy in technology integration (TPACK) and personal innovativeness in IT. In addition, it examined their perceptions of GenAI's usefulness and ease of use, key constructs within the Technology Acceptance Model (TAM). The findings contribute to a growing understanding of how higher education staff evaluate emerging technologies and may inform institutional strategies for supporting informed, faculty-driven integration of GenAI in teaching.

Hypothesis 1 predicted that TPACK self-efficacy would be positively associated with attitudes toward the use of GenAI in teaching. This was supported by the results, which showed a significant positive relationship between these variables. This aligns with prior work demonstrating that educators who feel confident in their ability to integrate technology into pedagogical practice are more likely to view new digital tools as legitimate and useful for instruction (Howard et al., 2021; Mah et al., 2025).

Hypothesis 2, which posited a positive relationship between personal innovativeness in IT (PIIT) and attitudes, was also supported. Lecturers with higher levels of innovativeness reported more favourable attitudes toward GenAI. This finding is consistent with those of Teo et al. (2019) and Sadallah (2025), who note that openness to experimentation is a strong predictor of receptiveness to emerging educational technologies.

The results also confirmed Hypotheses 3 and 4, which examined the relationships between perceived usefulness and ease of use, respectively, and attitudes toward GenAI. Both variables were positively associated with attitudes, indicating a significant and powerful effect. This pattern supports TAM-based research, which asserts that educators' evaluations of a technology's instructional value are central to shaping their attitudes (Baig & Yadegaridehkordi, 2025; Wang et al., 2024). Perceived ease of use was also significant, indicating that when lecturers feel that a tool can be incorporated into teaching without excessive effort or technical difficulty, they are more inclined to adopt positive attitudes (Titko et al., 2023; Mah et al., 2025).

The study further tested two mediation hypotheses. Hypothesis 5 proposed that perceived usefulness and ease of use would mediate the relationship between TPACK self-efficacy and attitudes. This was supported: the effect of TPACK on attitudes became non-significant when the mediators were included, indicating complete mediation. These findings suggest that pedagogical self-efficacy does not directly influence attitudes toward GenAI but instead operates by shaping how useful and usable the tool is perceived to be. This result aligns with prior studies suggesting that educators' confidence in their teaching with technology skills influences their interpretation of the instructional value of digital tools (Howard et al., 2021).

Hypothesis 6 proposed a similar mediation model for personal innovativeness in IT. This hypothesis was also supported, though the mediation was partial. Perceived usefulness and ease of use accounted for part of the relationship between PIIT and attitudes, but a significant direct effect remained. This finding supports the conceptualisation of PIIT as a relatively stable disposition that influences openness to technological change, even when specific features of the tool have not yet been evaluated (Teo et al., 2019; Sadallah, 2025).

Taken together, the findings underscore that academic staff's attitudes toward GenAI are shaped by both trait-like characteristics (e.g., innovativeness) and context-sensitive evaluations (e.g., usefulness). Notably, the study reveals that perceived usefulness plays a central role in these relationships, consistent with recent literature that highlights the primacy of perceived instructional relevance in higher education adoption decisions (Baig & Yadegaridehkordi, 2025; Wang et al., 2024).

The significance of perceived ease of use points to the importance of implementation simplicity and institutional clarity. When lecturers feel that a new tool aligns with existing teaching practices and can be integrated with minimal disruption, they are more likely to evaluate it favourably (Titko et al., 2023; Shankar et al., 2024). In this regard, attitudes are not shaped solely by technical properties, but by the match between the tool and professional pedagogical norms (Mah et al., 2025).

Finally, the complete mediation of TPACK self-efficacy and the partial mediation of PIIT highlight different pathways through which faculty traits shape attitudes. TPACK self-efficacy appears to influence attitudes only indirectly, by shaping the lens through which GenAI is evaluated. By contrast, PIIT exerts both direct and indirect effects, suggesting that faculty who are generally comfortable with experimentation may support new technologies even before perceiving them as particularly useful or easy to use. These distinctions may have important implications for institutional support strategies.

Practical Implications

The findings of this study have several practical implications for higher education institutions seeking to support the pedagogical integration of generative AI. First, the central role of perceived usefulness in shaping attitudes toward GenAI suggests that institutional efforts should highlight pedagogically relevant use cases. Rather than promoting GenAI as a general-purpose tool, guidance should focus on how it can concretely enhance teaching and learning, such as by streamlining formative feedback, generating examples, or supporting differentiated instruction (Mah et al., 2025; Sadallah, 2025). Demonstrating clear instructional benefits is likely to foster more favourable attitudes among lecturers, particularly those who remain cautious about new technologies.

Second, the significance of perceived ease of use indicates that implementation efforts must be accompanied by appropriate technical and pedagogical support. Institutions should ensure that staff have access to training that is both accessible and relevant to their disciplinary contexts. Faculty with limited time or confidence may be especially deterred if the technology appears complex or difficult to integrate (Titko et al., 2023; Shankar et al., 2024). Low-threshold entry points and practical walkthroughs are therefore critical to reducing barriers to engagement.

Third, the finding that TPACK self-efficacy influences attitudes through perceptions of usefulness and ease of use points to the value of strengthening lecturers' technological pedagogical competence. Professional development should not be limited to software demonstrations but should also reinforce instructional design skills for working with GenAI. As Baig and Yadegaridehkordi (2025) argue, faculty development programs that integrate pedagogy and digital fluency are more likely to succeed in fostering meaningful and sustained engagement.

Finally, the partial mediation observed in the case of personal innovativeness in IT suggests that not all faculty will require the same level or type of support. Those with higher innovativeness may be early adopters and can serve as peer mentors or champions. Identifying and empowering such individuals may help diffuse adoption more organically across departments (Teo et al., 2019). At the same time, institutions should avoid assuming uniform readiness and instead consider differentiated strategies that account for varying comfort levels and professional identities.

Limitations

Several limitations must be acknowledged. First, the study employed a cross-sectional design, collecting data at a single point in time. This precludes any inference of causality or temporal ordering among the variables. Although the mediation models tested are theoretically plausible, they cannot confirm directional effects.

Second, the sample was drawn from a single academic institution in Israel through an online survey distributed shortly after a semester break. It is possible that some lecturers did not report current engagement with AI-related teaching because they had not recently taught, even if they are otherwise active users. This timing issue may have influenced their responses.

Third, the measure used to assess personal innovativeness in IT was validated in prior literature (Al-Adwan et al., 2023). However, the instrument developed for this study to assess AI-related perceptions and attitudes, including actual usage, was not formally validated. Moreover, the mean level of reported AI usage was low, with limited variance.

Fourth, the sample included a small number of male lecturers (16.7%), and the sample size (n = 84) limits the capacity to conduct gender-based subgroup analyses or to apply advanced structural equation modelling techniques, as had been done in comparable student-focused research.

Finally, as with all self-report studies, the findings may be subject to response biases, including social desirability or differing interpretations of survey items. This may be especially relevant in a rapidly evolving domain like GenAI, where terminology and experience levels may vary widely.

Future Directions

Future research should build on this study by employing longitudinal or mixed-method designs to track how faculty attitudes toward GenAI evolve, as well as changes in institutional policies, student expectations, and pedagogical norms. Longitudinal data would also enable stronger causal claims and facilitate an examination of how initial attitudes translate into actual usage patterns.

Second, there is a need for research across diverse institutional and cultural settings. Recent work has shown that university responses to GenAI vary widely by context, with different expectations, support structures, and regulatory environments influencing faculty perspectives (Wang et al., 2024). Comparative studies would help identify institutional factors that facilitate or hinder positive engagement with GenAI.

Third, future studies should develop and validate dedicated instruments for assessing lecturers' attitudes, perceived barriers, and pedagogical intentions regarding GenAI. The rapid development of AI tools requires measurement tools that are context-sensitive, up-to-date, and psychometrically robust.

Fourth, given the limitations around sample size and gender distribution in this study, larger-scale studies with representative samples are needed. Such work would enable the analysis of potential subgroup differences and contribute to understanding whether demographic or disciplinary factors moderate the observed relationships.

Finally, qualitative studies, such as in-depth interviews or focus groups, could complement survey-based findings by exploring how lecturers interpret the pedagogical, ethical, and professional implications of GenAI. Understanding these interpretive frameworks is essential for designing institutional interventions that resonate with faculty values and concerns (Shankar et al., 2024; Mah et al., 2025).

Bibliography

Al Zaidy, A. (2024). Exploring Cybernetics Students' Perceptions of AI in Education: A Comprehensive Analytical Study. *Journal of Information Technology, Cybersecurity, and Artificial Intelligence*, *1*(1), 47-51.

An, Y., Yu, J. H., & James, S. (2025). Investigating the higher education institutions' guidelines and policies regarding the use of generative AI in teaching, learning, research, and administration. *International Journal of Educational Technology in Higher Education, 22*(1), 10. https://doi.org/10.1186/s41239-025-00417-3

Archambault, L., & Crippen, K. (2009). Examining TPACK among K–12 online distance educators in the United States. Contemporary Issues in Technology and Teacher Education, 9(1), 71–88.

Baig, M. I., & Yadegaridehkordi, E. (2025). Factors influencing academic staff satisfaction and continuous usage of generative artificial intelligence (GenAI) in higher education. *International Journal of Educational Technology in Higher Education, 22*(1), 5. https://doi.org/10.1186/s41239-025-00413-7

Barakat, A. (2024). Perspectives of university educators regarding ChatGPT: A validation study based on the technology acceptance model. *Education and Information Technologies, 29*, 1234–1250. https://doi.org/10.1007/s10639-024-12318-w

Barrientos, A., Del Mundo, M. A., Inoferio, H. V., Adjid, M. A., Hajan, H. B., Ullong, M. M., Alih, D. R. S., Abdulmajid, B. P., & Espartero, M. M. (2024). Discourse analysis on academic integrity generative AI: Perspectives from science and mathematics students in higher education. *Environment & Social Psychology*, 9(9). https://doi.org/10.59429/esp.v9i9.2927

Bates, A. W. (2020). Can artificial intelligence transform higher education? *International Journal of Educational Technology in Higher Education, 17*, Article 42. https://doi.org/10.1186/s41239-020-00179-x

Baytak, A. (2023). The acceptance and diffusion of generative artificial intelligence in education: A literature review. *Current Perspectives in Educational Research, 6*(1), 7–18. https://doi.org/10.5281/zenodo.10293800

Brislin, R. W. (1980). Translation and content analysis of oral and written materials. In H. C. Triandis & J. W. Berry (Eds.), Handbook of cross-cultural psychology: Vol. 2. Methodology (pp. 137–164). Boston, MA: Allyn and Bacon.

Chan, A. (2023). A comprehensive AI policy education framework for university teaching and learning. Computers and Education:

Artificial Intelligence, 4, 100132. https://doi.org/10.1016/j.caeai.2023.100132

Choung, H., David, P., & Ross, A. (2023). Trust and ethics in AI. AI & Society, 38(2), 733–745. https://doi.org/10.1007/s00146-021-01229-6

Class, B., & de la Higuera, C. (2024). From disposable education to acting in the world as a human in the time of AI. Journal of Ethics in Higher Education, 4, 231–244. https://doi.org/10.26034/fr.jehe.2024.5973

Deng, Q. (2023). Identifying key mentor characteristics in the use of AI-based tools for higher education. International Journal of Educational Technology in Higher Education, 20(1), 15. https://doi.org/10.1186/s41239-023-00380-y

Göçen, A., & Asan, R. (2023). Generative artificial intelligence: Risks and benefits for educational institutions. *Journal of Educational Technology & Online Learning, 6*(2), 103–117.

Hargarter, A. (2024). Leadership ethics and digital disruption in global universities. Journal of Ethics in Higher Education, 4, 91–122. https://doi.org/10.26034/fr.jehe.2024.5957

Hayes, A. F. (2017). Introduction to mediation, moderation, and conditional process analysis: A regression-based approach. New York, NY: Guilford Publications.

Howard, S. K., Tondeur, J., Siddiq, F., & Scherer, R. (2021). Ready, set, go! Profiling teachers' readiness for online teaching in secondary education. Technology, Pedagogy and Education, 30(1), 141–158. https://doi.org/10.1080/1475939X.2020.1837101

Ismail, M. (2024). Preparing teachers of the future in the era of artificial intelligence. *International Journal of Learning, Teaching and Educational Research, 23*(4), 45–60. https://doi.org/10.26803/ijlter.23.4.3

Jacques, P. (2024). A synthesis of AI in higher education: Shaping the future. *AI in Education Review, 1*(1), 22–37.

Kim, Y., Park, S., & Li, J. (2024). Generative AI in education: Opportunities and concerns from students and instructors. *Education and Information Technologies, 29*, 1215–1232. https://doi.org/10.1007/s10639-024-12306-0

Khanfir, H. (2024). Ethics, technology and social transformation in higher education. Journal of Ethics in Higher Education, 4, 123–142. https://doi.org/10.26034/fr.jehe.2024.5958

Khong, Y. L. (2023). Examining teachers' behavioural intention for online teaching after the COVID-19 pandemic: A large-scale survey. Education and Information Technologies, 28, 5999–6026. https://doi.org/10.1007/s10639-023-11889-5

Korcz, G., Amzaleg, M., Barak-Medina, A., Gal, O., Zaguri, Y., Zeiler, G., Cohen-Vaks, D., & Shaked, N. (2023, September). Higher education and generative AI: Background, opportunities, challenges, and recalibration – A position paper. HIT – Holon Institute of Technology. https://hit.ac.il

Kurtz, G. (2024). Generative artificial intelligence in Israeli higher education: Strategic perspectives and challenges. *Education, 14*(503), 1–13. https://doi.org/10.3390/education140503

Linden, T., Yuan, K., & Mendoza, A. (2025). The potential and challenges of integrating generative AI in higher education as perceived by teaching staff: A phenomenological study. *Information Systems Education Journal, 23*(3), 16–30.

Lindsay, J., & Jacka, L. (2024). The footsteps on the sands of AI for higher education: Moving beyond ad-hoc. Journal of Ethics in Higher Education, 5, 51–77. https://doi.org/10.26034/fr.jehe.2024.6863

McDonald, N., Johri, A., Ali, A., & Collier, A. H. (2025). Generative artificial intelligence in higher education: Evidence from an analysis of institutional policies and guidelines. *Computers in Human Behavior: Artificial Humans*, 100121.

Mohamed, M. S. P. (2024). Exploring ethical dimensions of AI-enhanced language education: A literature perspective. Technology in Language Teaching & Learning, 6(3), 1813-1813. https://doi.org/10.29140/tltl.v6n3.1813

Morandín-Ahuerma, F. (2024). Generative artificial intelligence in education: A dual-purpose tool. https://doi.org/10.31219/osf.io/2c3mr

Pavlik, J. V. (2023). Collaborating with ChatGPT: Considering the implications of generative artificial intelligence for journalism and media education. *Journalism & Mass Communication Educator, 78*(1), 84–93. https://doi.org/10.1177/10776958221149577

Preacher, K. J., & Hayes, A. F. (2008). Asymptotic and resampling strategies for assessing and comparing indirect effects in multiple mediator models. Behavior Research Methods, 40(3), 879–891. https://doi.org/10.3758/BRM.40.3.879

Sandra, S., Barros, J.-P., & Almeida, I. (2024). Impacts of generative artificial intelligence in higher education: Research trends and students' perceptions. *Education and Information Technologies, 29*, 1302–1319. https://doi.org/10.1007/s10639-024-12359-1

Selvaratnam, R., & Venaruzzo, L. (2024). Human-centered approach to the governance of AI in higher education: Principles of international practice. *Journal of Ethics in Higher Education*, 5, 79–102. https://doi.org/10.26034/fr.jehe.2024.6864

Shankar, K. (2024). Bringing teachers in the loop: Exploring perspectives on integrating generative AI in technology-enhanced learning. Journal of Ethics in Higher Education, 5, 103–122.

Smolansky, E., Cohen, A., & Inbar, D. (2023). Educator and student perspectives on the impact of generative AI: A qualitative study. *Higher Education Research & Development, 42*(5), 867–882. https://doi.org/10.1080/07294360.2023.2234567

Southworth, J., Migliaccio, K., Glover, J., et al. (2023). Developing a model for AI across the curriculum: Transforming the higher education landscape via innovation in AI literacy. Computers and Education: Artificial Intelligence, 4, 100127. https://doi.org/10.1016/j.caeai.2023.100127

Sudan, R., et al. (2024). Transformative learning with ChatGPT: Opportunities and challenges in faculty practice. The International Journal of Management Education, 22(1), 100932. https://doi.org/10.1016/j.ijme.2024.100932

Sudan, R., Arora, N., & Maheshwari, R. (2024). Ethical implications of using ChatGPT in education: A review of global perspectives. *Technology, Ethics and Education, 3*(1), 1–15. https://doi.org/10.1016/j.tee.2024.100017

Wang, H., Dang, A., Wu, Z., & Mac, S. (2024). Generative AI in higher education: Seeing ChatGPT through universities' policies, resources, and guidelines. *Computers and Education: Artificial Intelligence, 7*, 100326. https://doi.org/10.1016/j.caeai.2024.100326

Short Biography

Prof. Clara Hope Rispler, Department of Human Services and M.A. in Organisational Development and Consulting, The Max Stern Yezreel Valley College, clarar@yvc.ac.il

Dr. Michal Mashiach-Eizenberg, Department of Health Systems Management/M.A. program in Health Systems Management/MA in Nursing, The Max Stern Yezreel Valley College, michalm@yvc.ac.il

Dr. Gila Yakov, Department of Health Systems Management; Centre for Teaching Development, The Max Stern Yezreel Valley College, gilay@yvc.ac.il