

RESEARCH ARTICLE

Embracing the algorithm: Faculty perceptions of artificial intelligence tools and their role in transforming teaching and learning in higher education

A survey of foundation-programme faculty in a higher education institution in the Sultanate of Oman

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ABSTRACT

Although the use of Artificial Intelligence (AI) tools is a relatively recent phenomenon in the context of Higher Education (HE) practice, little research exists on the faculty in the Arab Gulf Region perceptions and application of AI tools. This study investigates the use of AI tools by academics in the foundation programmes at a Higher Education Institution (HEI) in Oman, the perceived value of AI in education and learning, challenges faced by these academics, and the professional development needs. A questionnaire with 40 questions was used for the quantitative, descriptive cross sectional survey from June to September 2026. Forty-four responses were received, of which eight (18.2%) were excluded because they were careless in their responses; the remaining 36 responses were analysed using descriptive and inferential statistics, as well as thematic analysis. Adoption of AI was widespread and commonplace, with 83.3% using AI tools at least weekly, with ChatGPT by far the most commonly used tool (91.7%), and the majority of users focusing on lesson planning (80.6%), teaching materials (77.8%) or the design of assessments (69.4%). Perceptions of pedagogical impact were rated as moderate ($M = 2.97$ on a scale of 5), and were bimodal, with barriers, primarily academic integrity ($M = 3.06$), there being around 50% at each end. Pedagogical impact was perceived at a moderate level ($M = 2.97$ of 5) and was bimodal, with academic integrity ($M = 3.06$) being the most common barrier endorsed by about 50% of the sample, followed by trustworthiness of content and cost. Younger, early career faculty reported significantly greater positive perceptions and much greater need for development ($p < .001$). The study reveals that there exists a practice-conviction gap between faculty use of AI and their confidence in the potential of AI as a pedagogical tool. Professional development, policy and assessment redesign, subsidized access, and connectivity and support are recommended to address the needs of individuals across the career stages.

KEYWORDS

artificial intelligence in education; faculty perceptions; generative AI; higher education; professional development; technology adoption; Oman

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1. Introduction

Artificial Intelligence (AI) has changed the setting for the delivery, assessment and governance of Higher Education (HE). Since then, intelligent tutoring systems, learning analytics, generative tools like ChatGPT, Microsoft Copilot and Google Gemini, have been growing in number at a pace that institutions can hardly keep up with when it comes to assessing their pedagogical implications (Zawacki-Richter et al., 2019). The effectiveness of institutional AI strategies in the classroom is shaped by faculty practices since they determine what will be assigned, how to assess and when to intervene (Popenici & Kerr, 2017).

Holmes and Tuomi (2022) define AIED as a multi-purpose, adaptable cluster of platforms, language processing software, predictive analytics and automated feedback mechanisms. After examining 146 studies, Zawacki-Richter et al. (2019) found that educators' perspectives were still significantly under-represented. Synthesised evidence shows that use of AI is concentrated in informal and peripheral activities and not in core pedagogical practice (Borgonovi et al., 2025); systematic evidence indicates that gains in engagement and personalization have occurred in interactive pedagogies where AI has been embedded (Kadaruddin, 2023; Long et al., 2026).

Individual, institutional and ethical aspects influence the adoption process (Popović Šević et al., 2025; Spathopoulou et al., 2025). Efficiency benefits and misconduct, reliance, fabricated content, and algorithmic opacity—these are just some of the double-edged sword effects of generative AI that are documented in appraisals. (Abdullah et al., 2025; Bittle & El-Gayar, 2025) Literature thus reaches a consensus that policy, training, and infrastructure that is reliable and stable constitute institutional scaffolding that makes integration responsible (Aguado-García et al., 2025; Malik et al., 2024).

The evidence base is still very young in the Arab and Gulf Cooperation Council (GCC) region. Fadlelmula and Qadhi (2024) found that, besides the ongoing challenges of teacher skills, infrastructure, resistance to change, and Arabic language processing, there were also institutional benefits. It has been reported by Natarajan et al. (2026) that there is a 'willingness-usage gap' at an Omani university, where attitudes were more advanced than competence. What is still lacking is a unified narrative—one combined design—about what faculty are doing with AI, their evaluation of its pedagogical merit, and what is hindering or needed for them in their support of AI, and how these change across career stages. The purpose of this study is to fill this gap within the faculty of foundation programme in an Omani Higher Education Institution (HEI), a challenging context characterized by immense teacher autonomy in carrying out the teaching and learning of the programme, large student cohorts, and high-pressure assessment. Four research questions guide the study:

- (1) To what extent and in what ways do faculty use AI tools in their teaching and learning-related activities?
- (2) How do faculty perceive the role of AI tools in enhancing their teaching effectiveness and students' learning outcomes?
- (3) What challenges and barriers do faculty face when integrating AI tools into their teaching?
- (4) What professional development and institutional support do faculty require to integrate AI tools effectively?

The study contributes an integrated account of usage, perception, barriers and development needs in an under-researched context, with recommendations aligned with Oman Vision 2040.

2. Literature Review

2.1 Conceptualising AIED and the technology-acceptance lens

AI in education (AIED) encompasses adaptive platforms, intelligent tutoring systems, generative AI and learning analytics. Holmes and Tuomi (2022) identified systems that support learners, empower teachers and manage institutions, and Zawacki-Richter et al. (2019) noted that the student perspective has prevailed in scholarship (Aguado-García et al., 2025; Popenici & Kerr, 2017). Usually, explanations for faculty adoption are based on the Technology Acceptance Model (TAM) which posits that attitude and intention to use are related to perceived usefulness and ease of use (Davis, 1989). When using AI in higher education, perceived usefulness has been consistently identified as the strongest predictor of intention, intermediate by attitude (Robinson, 2024; Xue et al., 2026). Two pitfalls also recur: the majority of TAM-studies of AIED are conducted with student samples without testing transferability to faculty; and 'use' is frequently equated with 'frequency', and not with 'quality'. Because this study is based on TAM's fundamental assumption of perceived usefulness, which implies high-quality use, it does not serve as a structural model.

2.2 AI tools and teaching effectiveness: evidence and its limits

The synthesis of 73 studies by Long et al. (2026) showed that the benefits of Chatbots, Adaptive systems and Predictive analytics are most profound in the context of interactive pedagogies specifically Flipped classroom and project-based learning, while Kadaruddin (2023) noted the potential of generative AI in personalized instruction and Aminah and Puspitasari (2023) recorded improvements in content customization and automated support. Evidence of outcomes is more mixed: Cao et al. (2025) found that adaptive AI leads to faster learning time and better outcomes but reports of variations in effectiveness based on domain and implementation fidelity. Research into the attitudes of faculty, teachers, and students towards conversational AI, conducted by Al-Zahrani (2025) on a sample of 524 faculty, teachers and students, did not limit the study to short-term, single course design, but did reveal faculty has a strong attitude towards conversational AI ($M = 4.01$ of 5).

2.3 Faculty perceptions, ethics and professional development

Junior faculty has been found to be more confident and more likely to adopt AI while senior faculty has been found to be more skeptical (Spathopoulou et al., 2025), and there has been a significant difference between users and non-users of AI tools (Popović Šević et al., 2025) with attitudes predicting intention more than demographic factors (Robinson, 2024). Ethical issues are also prominent: Abdullah et al. (2025) noted that generative AI can have a significant impact on academic integrity, and Bittle and El-

Gayar (2025) highlighted the interconnected risks of misconduct, overreliance, hallucination and privacy. Infrastructure, professional development and governance are essential for realizing the potential of AI (Aguado-García et al., 2025; Malik et al., 2024). The technical, critical, ethical and practical competences in the AI-literacy literature (Ng et al., 2021) provide the conceptual basis for this needs assessment, while instruments validated in the literature (Sanchez et al., 2025; Vera, 2023) offer a measure for this needs assessment.

2.4 The Gulf context and identified gaps

In other areas of the GCC clear evidence of advantages and disadvantages of language processing for teachers emerges in the existing literature: Fadlelmula and Qadhi (2024) synthesized 32 studies and found that teachers were more likely to experience positive effects, as well as barriers, including teacher skill, infrastructure, resistance, and Arabic-language processing; Natarajan et al. (2026) reported moderate levels of positive attitudes and moderate levels of use among teachers in Oman. Few studies have addressed usage, perception, barriers and development needs in a single instrument, career-stage differences have been reported in Western samples, and careless responding, a material threat to online AI surveys, is almost never reported.

3. Methodology

3.1 Design, context and participants

A quantitative, descriptive cross sectional survey design was used which allowed for the systematic gathering of numerical data from a population and the comparison of subgroups, without experimental manipulation (Creswell & Creswell, 2018). It was carried out in the foundation programmes of one Omani institution that has high enrolment and a standardized assessment system. The participants were full-time foundation faculty who were invited to participate through open recruitment using official email and learning-management-system (LMS) announcements, and all who responded were selected based on a screening process described below. It is not stratified random sampling, but rather purposive, voluntary response sampling, which leads to limited generalisability. The study was planned to achieve 200 responses, but according to the guidelines by Krejcie and Morgan (1970) 44 responses were received of which 36 were used for all inferential results reported, and corroboration was done using non-parametric techniques (Section 6.3).

3.2 Instrument, validity and reliability

A questionnaire consisting of 6 parts with 40 items developed by the researcher was used to gather data. In Part I, gender, age, academic rank, teaching experience, AI tools familiarity (field) and self-rated familiarity (I) were recorded. The current use (employment of AI tools, frequency and tools used and activities supported, both multiple response) was addressed in Part II. Parts III through V were the perceived effect on teaching and learning (Q11-Q20), barriers to integration (Q21-Q30), and the development needs (Q31-Q37) and were measured on a five-point Likert scale from 1 (Strongly Disagree) to 5 (Strongly Agree) (Cohen et al., 2018). Part VI consisted of an open-ended item asking participants about the biggest benefit and problem of using AI (Q39 and Q40) and one multiple-response item regarding the participants' preferred development formats (Q38). Items were based on validated instruments, with Part III-V answering Research Questions 2-4, and Part II, answering Research Question 1 (Sanchez et al., 2025; Vera, 2023). A panel of 5 subject-matter experts was consulted to validate the content with retention index of .78 or higher and an average score of .90 or higher at item and scale level respectively (Yusoff, 2019). The instrument was tested with 30 faculty from the same faculty as the survey respondents, but the responses from these faculty were not analyzed, so that no guarantee can be given that pilot sample faculty and analytic sample faculty responded to the same sample were sampled from one population. The internal consistency was excellent with alpha scores of .95, .96 and .97 for perceptions, barriers and development needs; and alpha scores of .97-.98 for the entire dataset (George & Mallery, 2019), although caution must be exercised due to the short scales and potential for response styles.

3.3 Procedure, screening and analysis

The questionnaire was distributed through official channels of the institution via Google Forms, and the email reminders left it open for around 3 months from 22 June to 23 September 2026, after institutional ethical approval. The purpose of the study and how it was voluntary, the right to withdraw and anonymity (Creswell & Creswell, 2018) were explained by a cover letter. Personal data was not gathered; the data was kept safely and transferred to the IBM SPSS Statistics (Version 26). As online surveys can be susceptible to careless responding, the data was screened first. Out of 44 submissions, 8 (18.2%) had no within-person differences in responses across all 27 Likert items (identical responses to each item in terms of content or direction); some even reported using multiple tools daily and found AI to be a great help in comments, suggesting inner contradiction without coherent evaluation. Primary analyses were repeated with the total sample as a robustness check—with the straight-lining cases excluded from the analyses. The other kept response was contradictory in regard to current AI use and was therefore kept due to the remaining consistent items. Mean item scores for the perceptions (10 items) and barriers (10 items) and development needs (7 items) were placed into five bands, ranging from very low (1.00–1.80) to very high (4.21–5.00). Independent-samples t tests

(Welch's correction) and Mann–Whitney U tests were used to compare subgroups by gender and age and experience, analysis of variance was used to compare familiarity levels, and Pearson correlations were used to explore associations among composites, with Cohen's d used to quantify the effect size. Non-parametric results are presented in addition to parametric results, since all three composites were shown by Shapiro-Wilk tests to be non-normal ($p = .020 - < .001$). Counting and percentages were calculated for multiple response items and inductive thematic analysis (Cohen et al., 2018) was used to analyse open-ended responses.

4. Results

4.1 Respondent profile and RQ1: extent and nature of AI use

A total of 44 questionnaires were submitted, eight (18.2%) were excluded because of careless respondents leaving an analyzable sample of 36 (Table 1). The cohort was early-career with 44.4% having less than 5 years' experience and 94.4% at lecturer level. More than half (52.8%) considered themselves very familiar with AI tools, while three who said 'not familiar at all' said they used AI tools daily or almost daily anyway.

Using AI was 'every day' or 'several times a week' rather than 'occasionally': 44.4% would use AI on a daily basis, while an additional 38.9% used it several times a week, with 83.3% using AI at least once per week. Conversational platforms were the most common methods for adopting AI tools (Table 2): ChatGPT (91.7%), Google Gemini (72.2%) and AI-writing detectors like Turnitin (69.4%) and Microsoft Copilot (50.0%). Specialized tools were less common; presentation tools (47.2%), video generators (27.8%) and quiz tools (22.2%). In preparatory work, it was used in lesson and course planning (80.6%), teaching materials (77.8%) and creating assessment or quiz (69.4%) and it was the least frequently used in administrative work (30.6%) and providing feedback (50.0%). The student facing work of feedback and conversation linked to student learning gains was thus only given partial attention.

Table 1
Respondent profile (N = 36)

Variable	Category	n	%
Gender	Female	20	55.6
	Male	16	44.4
Age	Under 30 years	13	36.1
	30–39 years	15	41.7
	40–49 years	8	22.2
Academic rank	Lecturer / instructor / teaching assistant	34	94.4
	Assistant professor	2	5.6
Teaching experience	Less than 5 years	16	44.4
	5–10 years	11	30.6
	11–20 years	8	22.2
	More than 20 years	1	2.8
Familiarity with AI tools	Very familiar	19	52.8
	Moderately familiar	9	25.0
	Slightly familiar	5	13.9
	Not familiar at all	3	8.3
Frequency of AI use	Daily	16	44.4
	Several times a week	14	38.9
	Once a week	3	8.3
	Rarely	2	5.6
	Occasionally	1	2.8

Note. Percentages may not total 100 because of rounding.

Table 2
AI tools used and teaching activities supported (N = 36)

Item	n	%
Panel A: AI tools used		
ChatGPT	33	91.7
Google Gemini	26	72.2
Turnitin / AI writing detectors	25	69.4
Grammarly	20	55.6
Microsoft Copilot	18	50.0
AI presentation tools (Gamma, Beautiful.ai)	17	47.2
AI video tools (Synthesia, HeyGen)	10	27.8
AI quiz/assessment tools (Quizgecko, Kahoot AI)	8	22.2
Panel B: Teaching activities		
Lesson / course planning and design	29	80.6
Preparing teaching materials	28	77.8
Creating assessments or quiz questions	25	69.4
Communicating with students	21	58.3
Conducting research / reviewing literature	20	55.6
Providing feedback to students	18	50.0
Administrative tasks	11	30.6

Note. Multiple-response items; percentages of respondents. Niche tools named once (Blooket, Bamboozle, Edpuzzle, Padlet) are omitted.

4.2 RQ2: Perceptions of AI's role in teaching and learning

Perceptions were moderate and highly polarized with a composite mean score of 29.67 of 50 (SD = 12.31) and a mean item score of 2.97. Most highly agreed upon items related to general attitude and self-efficacy: 'Overall, AI has a positive impact on teaching' (agreeing 58.3%) and 'Using AI tools increases my confidence as a teacher' (agreeing 55.6%). Weaker endorsement was garnered in more specific pedagogical claims: engagement (M = 3.08), learning outcomes (M = 3.06) and critical thinking (M = 3.06). The items with the lowest endorsement ratings were the most specific: using AI to improve lessons (M = 2.53), feedback (M = 2.78) and saves time (M = 2.81) (Table 3). On each item, there was a broad range of responses (SD = 1.26–1.70), and a highly bimodal distribution: 38.9% in the high band (mean item ≥ 3.41), 36.1% in the low band (≤ 2.60), and 25% in the middle band (Figure 2).

Table 3
Item-level descriptive statistics, ranked by mean within each construct (N = 36)

Item (abbreviated)	M	SD	% agree
Panel A: Perceptions of AI's role			
Overall positive impact on teaching	3.22	1.53	58.3
Increases my confidence as a teacher	3.17	1.40	55.6
Supports students' engagement in learning	3.08	1.40	50.0
Enhances student learning outcomes	3.06	1.26	47.2
Stimulates students' critical thinking	3.06	1.26	47.2
Enhances students' personal learning	3.06	1.47	44.4
Easier and more diverse assessment design	2.92	1.48	41.7

Item (abbreviated)	M	SD	% agree
Crucial to planning and delivery; saves time	2.81	1.69	50.0
Delivers better feedback to students	2.78	1.51	41.7
Helps create more effective lessons	2.53	1.70	41.7
Panel B: Barriers to integration			
Concern about academic integrity	3.06	1.51	50.0
Trustworthiness of AI-generated content	2.81	1.37	41.7
AI tools and subscriptions too expensive	2.81	1.49	44.4
Privacy and data-security concerns	2.69	1.37	41.7
Poor connectivity / technical infrastructure	2.67	1.41	41.7
Fear that AI harms students' learning skills	2.67	1.41	38.9
Lack of clear institutional policy	2.64	1.40	38.9
Not enough institutional support	2.61	1.25	30.6
Limited personal knowledge and skills	2.36	1.33	27.8
Unsure which tools suit my subject	2.31	1.24	25.0

Note. 1 = strongly disagree to 5 = strongly agree; % agree combines Agree and Strongly agree.

4.3 RQ3: Barriers to integration

Overall, barriers were rated as moderate-low (composite M = 26.61 of 50, SD = 11.81; mean item 2.66) and their profile is instructive (Table 3). Academic integrity was the strongest response with half of the sample (50.0%) saying they were concerned with academic integrity (M = 3.06, SD = 1.51). Concerns about trustworthiness of content (M = 2.81; 41.7%) and cost (M = 2.81; 44.4%) followed, then privacy (M = 2.69), connectivity (M = 2.67), harm to students' learning skills (M = 2.67) and absent policies (M = 2.64). Limited knowledge (M = 2.36) and uncertainty about tool selection (M = 2.31) were the least endorsed items with less than 30% endorsement and were considered internal deficits. Perceived value was positively correlated with barriers ($r = .53$, $p = .001$).

4.4 RQ4: Professional-development and support needs

Demand was moderate on average (composite M = 20.58 of 35, SD = 10.03; mean item 2.94) but strongly divided: 50.0% of respondents fell in the high band (mean item ≥ 3.41) and 41.7% in the low band (≤ 2.60). Peer learning (M = 2.94), workshops (M = 2.92) and technical support (M = 2.97) and clear policies that would license more confident use (M = 2.97) were endorsed by about half while free or subsidized AI tools (M = 3.08), guidance on proper use (M = 3.06) and formal learning opportunities (M = 2.64) received the strongest support (Table 4). The wishes of the faculty were clear: face-to-face workshops (91.7%), online self-paced courses (69.4%), mentoring and peer support (66.7%) and live webinars (61.1%) were far more popular than the written guidelines, which were selected by only 36.1%, indicating that faculty preferred to see policy reflected in practice rather than in writing.

Table 4
Professional-development needs and preferred formats (N = 36)

Item	M / n	SD / %
Panel A: Development needs (1–5)		
Access to free or subsidised AI tools	3.08	55.6
Learning proper ways to use AI	3.06	55.6
Institutional technical support	2.97	50.0
Clear policies would increase my use	2.97	50.0
Peer learning / exchange of good practice	2.94	52.8

Item	M / n	SD / %
Institutional workshops and courses	2.92	50.0
Formal learning on using AI	2.64	47.2
Panel B: Preferred formats		
Face-to-face workshops	33	91.7
Online self-paced courses	25	69.4
Mentoring and peer support	24	66.7
Webinars and live online sessions	22	61.1
Institutional guidelines and manuals	13	36.1

Note. Panel A: means and % agreeing. Panel B: % selecting each format.

4.5 Associations, reliability and group differences

Construct means are presented in Figure 1, and the constructs were highly intercorrelated such that correlations between the constructs (perceptions with barriers, $r = .53$, $p = .001$; perceptions with development needs, $r = .55$, $p = .001$; and barriers with development needs, $r = .58$, $p < .001$) were significant. No familiarity effect was found on perceptions ($r = .09$; $p = .185$ -.963), barriers ($r = .06$; $p = .185$ -.963) or development needs ($r = -.18$; $p = .185$ -.963) while there was no usage frequency effect on perceptions ($r = -.03$; $p = .185$ -.963). However, there were differences in responses by career stage (Table 5). Faculty aged 30 and over ($n = 23$) held weaker perceptions than those under 30 ($n = 13$; $M = 25.30$, $SD = 12.54$ vs. $M = 37.38$, $SD = 7.26$; $t = -3.66$, $p = .001$, $d = -1.10$; $U = 63.0$, $p = .005$), and the pattern was more pronounced for development needs ($M = 29.46$ vs. 15.57 ; $t = -6.49$, $p < .001$; $d = -1.85$). There was no strong age difference in the barriers (parametric $p = .048$; non-parametric $p = .207$). Experience mirrored age: respondents with five or more years reported weaker perceptions ($M = 24.85$ vs. 35.69 ; $t = -3.04$, $p = .005$; $d = -0.97$) and weaker development needs ($M = 16.05$ vs. 26.25 ; $t = -3.55$, $p = .001$; $d = -1.17$), with no difference in barriers. There were no significant differences between the genders ($p = .154$ -.782). Robustness checks on all 44 responses strengthened these effects ($t = -3.21$ to -7.94 , $p = .003$ to $< .001$).

Table 5
Composite scores by age and teaching experience

Construct / group	n	M	SD	t	p	d
Perceptions						
Under 30 years	13	37.38	7.26	-3.66	.001	-1.10
30 years and over	23	25.30	12.54			
Development needs						
Under 30 years	13	29.46	3.86	-6.49	< .001	-1.85
30 years and over	23	15.57	8.88			
Perceptions (experience)						
Less than 5 years	16	35.69	8.01	-3.04	.005	-0.97
5 years or more	20	24.85	13.18			
Development needs (experience)						
Less than 5 years	16	26.25	7.91	-3.55	.001	-1.17
5 years or more	20	16.05	9.33			

Note. Perception range 10–50; development needs 7–35. Welch's t tests, confirmed by Mann–Whitney U tests ($p \leq .011$) except barriers, which did not differ reliably by group.

4.6 Thematic analysis of open-ended responses

Twenty two (61.1%) respondents made substantive comments, which led to five advantage themes and eight difficulty themes (Table 6). The most prevalent benefit was the personalized, adaptive learning aspect, 'it makes learning more personalized ... it can help meet students' different learning needs', and the efficiency in planning and 'repetitive tasks'. Other benefits were better teaching resources and quicker feedback, with one response stating that students could 'skip doing the assignments on their own' was a benefit. The most common difficulty faced by teachers stemmed from accuracy and verifiability (nine respondents), with one mathematics teacher stating that 'incorrect explanations or calculations can confuse students'; lack of training and integration know-how was the next most frequently mentioned issue, with one teacher adding that 'students are overly dependent on AI and need to learn how to use it within an academic context'. Academic integrity and student overdependence were next, including the statement 'students should be able to use AI but still be able to think critically for themselves'. As always, cost, privacy, infrastructure and the absence of policy came into play, as did concerns about the loss of human judgment: 'it is my job to be sure of the material produced by AI.'

Table 6
Themes from open-ended responses (22 respondents)

Theme	n	Illustrative quotation
Advantages		
Personalised / adaptive learning	10	"it makes learning more personalized ... meet students' different needs"
Time efficiency in routine tasks	7	"save time and effort ... in repeated tasks"
Better resources and engagement	7	"a wide range of ideas"; "make classes interactive"
Faster feedback and student support	7	"provide immediate feedback"
Idea generation and problem solving	2	"solutions to unexpected obstacles"
Difficulties		
Accuracy and fabricated content	9	"incorrect explanations or calculations can confuse students"
Lack of training / integration know-how	8	"lack of sufficient training and experience"
Integrity, over-dependence, human judgement	6	"as an instructor, it is my job to authenticate the material created by AI"
Data privacy and security	4	"concerns about data privacy"
Cost and limited free access	4	"some AI tools are too expensive"
Infrastructure and connectivity	2	"lack of high quality internet connection"
Absence of policy	2	"the lack of policy"
Erosion of creativity / contextual fit	1	"fear of losing creativity"

Note. Responses could be coded to multiple themes.

Figure 1. Mean item scores and standard errors for the three constructs (N = 36)

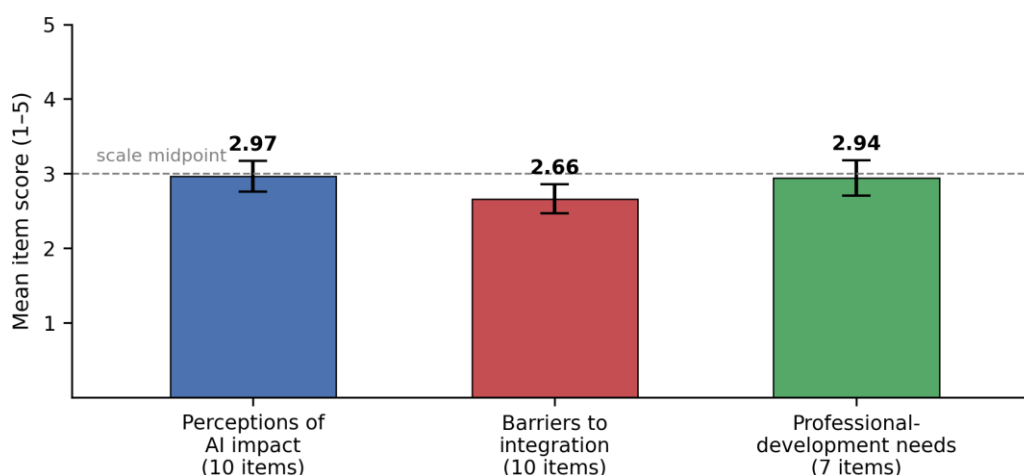
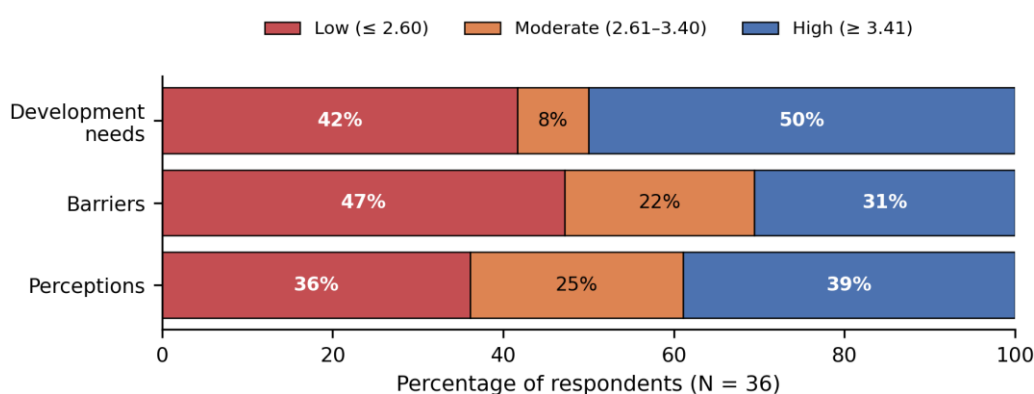


Figure 2. Distribution of respondents across score bands by construct (N = 36)



5. Discussion

5.1 Routine adoption with a narrow pedagogical reach

The central question is that of the intersection of – and indeed the co-existence of – routine use of AI and moderate but contested pedagogical conviction. Over four out of five used the AI at least once a week, but not in the form of informal uses, as described internationally (Borgonovi et al., 2025), but in planning, materials and assessment. However, the rate of adoption is not as high as it might seem, as it focuses in the preparatory aspects of teaching that the student cannot see, but becomes less common in the student-facing aspects of teaching, such as feedback and engagement. This is an exact opposite of what Long et al. (2026) warn against: that engagement is related to integration within interactive pedagogies and not frequency of use, meaning that faculty seem to use AI to do current work in a quicker manner, not to reconfigure the pedagogical encounter.

5.2 Moderate, polarized perceptions and the practice-conviction gap

The pedagogical value of AI (2.97) does not match the strongly positive attitude mentioned earlier, for example in Al-Zahrani's (2025) study, which had a faculty mean of 4.01, and the distribution is not consensual, but rather bimodal. Two implications follow. First, perceived usefulness seems domain-differentiated, meaning that faculty may be more likely to believe in the general impact and general confidence in the use of AI for their work than its specific consequences for lessons, feedback or time saving; thus, some of the motivational predictions of TAM may apply to this, but not to the latter. Perceived usefulness also seems domain-differentiated, with faculty endorsing general impact and general confidence more strongly than specific consequences for lessons, feedback or time saving; so, some motivational predictions of TAM may apply, but not the latter. Second, the data reveal that the gap between willingness and usage, reported in Oman by Natarajan et al. (2026), is reversed; that is, the attitudes are not as strong as the usage is. Administrative expectation and free conversational tools and workload pressures that incentivize speed are plausible explanations, and so is reliance on habit, not necessarily on evidence-based conviction, for integration.

5.3 Barriers as engaged skepticism, and the career-stage divide

The barrier profile questions the notion of ignorance as a cause of resistance. The three elements that emerged as the most prominent, whether negative or positive, were academic integrity, trustworthiness of content and cost, with internal deficits of knowledge and tool selection being the weakest barriers, and barriers having a positive correlation with perceived value ($r = .53$). This sparked skepticism, which aligns with the evidence of generative AI introducing real integrity and accuracy concerns as well as productivity benefits (Abdullah et al., 2025; Bittle & El-Gayar, 2025; Malik et al., 2024). It is therefore less likely that motivating interventions are going to be a restriction; rather, policy clarity, integrity protocols and verification support are more relevant (Fadlelmula & Qadhi, 2024). The most robust finding is a difference in career stage, with younger and less-experienced faculty expressing significantly more positive perceptions and very significantly more career needs when compared to their peers from Spathopoulou et al. (2025) and in reading of the willingness-usage gap as a competency gap across generations. Early-career faculty might be more receptive, but they also might be more aware of the gap in their competences, while experienced faculty may have established a “routine” that results in less perceived need for training. This lack of predicting any outcome ($r = .09$ to $-.18$) further supports the worry that it is not a strong indicator of competence (Ng et al., 2021).

5.4 Implications for theory, measurement and practice

According to the theoretical possibilities the practice-conviction gap and the domain-differentiated perceived usefulness indicate that models of AI acceptance should distinguish general attitudes from task-specific beliefs and between use and conviction. Methodologically, the danger of important casualty items from careless responding is evident in online AI surveys: 18.2% of all responses reported a zero within-person variance on 27 items, and reliability coefficients that were not cleaned were implausibly high, and thus, routine screening and clear reporting is warranted (Meade & Craig, 2012). In practice, the limitations are not the lack of enthusiasm but of convictions, policy and resourcing (Aguado-García et al., 2025; Ng et al., 2021).

6. Conclusions and Recommendations

6.1 Conclusions

There are four conclusions drawn from the present study. The first is that the use of AI is not new or exceptional: The 83.3% who used AI at least weekly, while conversational tools are now considered common instruments of preparation and assessment design. Second, the regular practice side by side with moderate and polarized conviction leads to a practice-conviction gap in which practice outpaces conviction. Third, the impediments that are most important are ethical and material - integrity, trustworthiness of content and cost - not lack of knowledge, and they are most strongly felt by the most purposeful users. Finally, need is partitioned according to career stage: younger, less experienced faculty show more positive perceptions and report significantly higher needs for professional development; and self-assessed knowledge predicts no outcome. The next phase of integration is thus not one of increasing use, but of strengthening the use of existing practices, supporting it more adequately and clearly regulating it.

6.2 Recommendations

Policy and governance. The Institution should have a clear and readable AI policy that outlines acceptable and unacceptable practices related to learning and assessment, and transparency requirements and data protection limits, with half of the sample saying that policy would boost their use, while the same number also reported concerns about integrity issues; policy would be both facilitative and protective (Abdullah et al., 2025; Bittle & El-Gayar, 2025). Professional development should be practice-focused, grade level and discipline-specific, with 91.7% stating they would prefer face-to-face workshops and 66.7% indicating they would want mentoring (for both early and experienced faculty); early career faculty might benefit from a structured induction period in planning, assessment design, verification practice and AI literacy, and experienced faculty may benefit from short clinics on choosing tools and redesigning assessments. Content to be developed should focus on critical and ethical competences, rather than operational skill (Ng et al., 2021) and complement one-off events with communities of practice (Aguado-García et al., 2025).

Integrity of access, infrastructure and assessments. Equitable integration requires licensing, affordable access, stable internet connection, and language laboratory supports, along with a clear technical-support channel with a guide to prompting and verification (Fadlelmula & Qadhi, 2024). Assessments should also be redesigned to focus on process rather than the outcome and to make thinking visible e.g. staged submissions, in-class components, oral defense, to ground in the principles of responsible use of AI with faculty supported to teach explicitly and to emphasize the process of producing the assignment and not the outcome. In view of self-reported use, institutions should also conduct periodic evaluations of AI-literacy based on validated tools (Sanchez et al., 2025; Vera, 2023) and at the same time on objective usage analytics, in accordance with national digital-transformation goals (Natarajan et al., 2026).

6.3 Limitations and future research

These are qualified by four limitations. The sample consisted of 36 analyzable responses, from the foundation programmes of a single institution, and few changes in rank and discipline, meaning the results are contextually informative but not generalizable; thus, inferential results are reported using effect sizes and non-parametric corroboration. This is a cross-sectional, self-reported design, which does not allow for any causal inference as to whether the use of AI affected teaching quality. The pilot sample and the analytic sample were both taken from the same faculty population, and therefore careless responses and some construct-irrelevant variance may exist, as eight (18.2%) responses were ruled out as careless. Lastly, only 22 respondents gave short answers to the open-ended questions. Future studies should continue to investigate multi-institution samples, validated AI-literacy scales, objective usage measures, longitudinal studies and quasi-experimental studies that connect pedagogies that incorporate AI to student outcomes.

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