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Research Article

A detailed examination of faculty acceptance of artificial intelligence: Insights from key variables

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The adoption and use of emerging technologies like artificial intelligence (AI) in universities can significantly impact educational and research processes. This study investigates the acceptance levels of AI technologies among university faculty members in Türkiye using a descriptive survey design. Data were collected via convenience sampling during the spring semester of the 2023-2024 academic year from 392 faculty members through an online questionnaire distributed by email. The AI Acceptance Scale, developed based on the Technology Acceptance Model, was employed to measure acceptance levels. Data analysis included descriptive statistics, normality tests, and non-parametric inferential analyses conducted via SPSS 26.0. Findings indicated a high level of AI acceptance overall, with sub-factors showing high scores for ease of use, perceived usefulness, attitude toward use, and intention to use. Age and duration of AI use were found to significantly affect acceptance levels. These results provide valuable insights for facilitating AI integration in higher education environments.

Keywords: Artificial intelligence, acceptance, higher education, university faculty members

1. Introduction

AI is a multidisciplinary field that has evolved significantly over the past decades, encompassing areas such as machine learning, natural language processing, and robotics (Russell & Norvig, 2021). Foundational works in AI, including Goodfellow et al.'s (2016) comprehensive exploration of deep learning, provide the theoretical underpinnings for contemporary AI applications. As Kaplan and Haenlein (2019) note, AI technologies range from simple rule-based systems to advanced cognitive agents capable of complex decision-making and learning.

The technology acceptance model (TAM), developed by Davis (1989), posits that perceived ease of use and perceived usefulness are critical determinants of technology adoption. In the context of AI in education, studies have applied TAM to assess faculty members' acceptance levels. For instance, Tekin (2024) extended TAM by incorporating self-efficacy and AI anxiety, finding that perceived ease of use and usefulness significantly influenced behavioral intentions to use AI technologies. Similarly, Runge et al. (2025) emphasized the role of AI-related teacher training courses and AI-TPACK in enhancing pre-service teachers' acceptance of AI tools.

In higher education, AI is transforming various aspects of universities and instructional methods. AI-driven personalized learning platforms adapt content and pacing to individual student needs, improving engagement and outcomes (Zawacki-Richter et al., 2019). Automated grading and feedback systems reduce faculty workload while providing timely responses to students (Balfour, 2013). AI-powered chatbots and virtual assistants offer 24/7 support, facilitating administrative tasks and learner interactions (Fryer et al., 2021). Furthermore, AI analytics enable early identification of students at risk, allowing targeted interventions to improve retention and success (Arnold & Pistilli, 2012). In research, AI tools assist in literature review, data analysis, and even hypothesis generation, accelerating scholarly productivity (Baker & Smith, 2019).

To effectively leverage AI's potential, universities and educators must develop comprehensive strategies. This includes faculty development programs that enhance AI literacy and technical skills (Luo et al., 2020), investments in infrastructure to support AI integration (Holmes et al., 2019), and the establishment of ethical guidelines to address privacy, bias, and transparency concerns (Floridi et al., 2018). Encouraging research into AI pedagogy and its impact on learning will further inform best practices and policy development.

The integration of Artificial Intelligence into higher education is transforming teaching, learning, and administrative processes globally. In Türkiye, the Higher Education Council has initiated AI-focused programs, including 21 undergraduate and 50 associate degree programs across 20 universities for the 2024–2025 academic year (Özvar, 2024). This national strategy underscores the urgency of understanding AI acceptance among academic staff to facilitate effective implementation. In Türkiye, research on AI acceptance among university faculty is gradually emerging. A study by Karaoglan-Yılmaz et al. (2023) developed a Generative AI Acceptance Scale grounded in the Unified Theory of Acceptance and Use of Technology [UTAUT], highlighting the importance of performance expectancy, effort expectancy, and social influence in faculty members' acceptance of generative AI applications. These findings align with international studies, suggesting that faculty members' attitudes toward AI are influenced by both individual perceptions and institutional support structures. On top of these advancements, there is a paucity of research focusing on Turkish faculty members' AI acceptance, particularly in the context of private universities. This study aims to fill this gap by examining the acceptance levels of AI technologies among faculty members, providing insights into the factors influencing AI adoption in Turkish higher education institutions.

1.1. Applications of Artificial Intelligence

AI currently delivers effective results across a broad spectrum of applications in sectors such as healthcare, finance, education, and customer service. In healthcare, AI systems developed by Google DeepMind have demonstrated diagnostic success rates for eye diseases comparable to those of expert doctors, showcasing the potential of this technology (De Fauw et al., 2018). Similarly, the contributions of AI to enhancing competitive advantages and fostering collaboration in business are widely recognized (Xiong et al., 2020). Kanbach et al. (2023) emphasize that AI redefines business models by offering innovative solutions. In the retail sector, AI is widely used for analyzing customer needs, while in education, it facilitates personalized learning environments. These applications are among the key drivers behind the rapid adoption of AI (Bhagat et al., 2022; Wu et al., 2022). More recent advances further demonstrate AI's expanding impact. For example, Hassan et al. (2024) highlight AI-driven predictive analytics transforming supply chain management by optimizing logistics and reducing waste. In finance, Yaseen et al. (2025) illustrate how AI algorithms enhance fraud detection and risk assessment, increasing security and efficiency in digital transactions. In education, AI-based adaptive learning platforms that dynamically tailor content to individual student profiles significantly improve engagement and academic outcomes (Bello & Olufemi, 2024). These developments underscore AI's growing role as a critical enabler of innovation and efficiency across diverse domains.

1.2. Applications of AI in Education

Arslan (2020) categorized artificial intelligence tools into three main groups: intelligent tutoring systems, expert systems, and dialogue-based tutoring systems. These tools are effectively used not only to support learning but also in assessment, classroom management, and administrative tasks. AI-powered systems facilitate the automation of administrative duties, reducing the workload of educators and administrative staff, thereby enabling them to utilize their time and energy more efficiently. Berkat (2024) highlighted in their study that AI has gained widespread acceptance in corporate training and supports learning processes. At the K-12 level, Casal-Otero et al. (2023) argued that fostering AI literacy from an early age is a critical need for future generations.

At the higher education level, the adoption and use of AI have introduced new skill requirements for both students and faculty. AI enhances the efficiency of teaching processes by supporting learning experiences (Solanke, 2024). Alrashedi and Abbod (2020) demonstrated that

AI improves accuracy in administrative processes at universities, while Popescu et al. (2023) revealed that AI-based chatbots enhance student engagement, creating an innovative impact within academic environments. Studies on the use of generative AI tools like ChatGPT in higher education emphasize the need to address ethical concerns and establish usage standards in the integration of AI into education (Hashmi & Bal, 2024; Michel-Villarreal et al., 2023).

Research conducted in Türkiye and globally has yielded positive outcomes regarding the use of AI in education and analyzed the acceptance levels of AI among teachers and students. Among the studies conducted in Türkiye, Kılavuz (2024) examined teachers' acceptance of AI tools like ChatGPT in terms of demographic variables, while Dülger (2023) analyzed the influence of factors such as age and seniority on AI acceptance in school settings. On a global scale, Mabuan (2024) explored teachers' positive perceptions of ChatGPT's use in language teaching, and Petricini et al. (2024) analyzed perceptions and risks associated with the use of AI in higher education. These studies are crucial for understanding the potential benefits of AI in education and its acceptance processes.

1.3. Technology Acceptance Model

TAM provides a significant theoretical framework for understanding the level of AI adoption. Developed by Davis (1989), TAM explains users' acceptance of technology through the components of "perceived usefulness" and "perceived ease of use." Venkatesh and Davis (2000) expanded the model by introducing TAM 2, which includes factors such as social influence and job relevance. Later, the Unified Theory of Acceptance and Use of Technology examined the effects of demographic characteristics such as age and gender (Venkatesh et al., 2003). These models serve as a guide for understanding and facilitating the acceptance and effective integration of AI in education.

In this context, this study aims to understand the process of AI acceptance in higher education and to examine the extent to which academic staff adopt this technology based on various variables. Accordingly, the study seeks to answer the following research questions:

RQ 1) To what extent do university lecturers accept AI tools?

RQ 2) Does the acceptance of AI tools by academic staff vary based on factors such as gender, age, years of professional seniority, academic title and type of institution?

2. Method

In this study, the descriptive survey method, which is used to quantitatively explain the relationships among multiple variables from the past or present and the level of these relationships, was employed (Cohen et al., 2000).

2.1. Research Design and Participants

This study employed a descriptive survey design to investigate university faculty members' acceptance of AI technologies. Data were collected using a convenience sampling method from 392 academic staff working at two universities in Türkiye, one of them was public, while the other was private. The data collection took place during the spring semester of the 2023-2024 academic year. Participants included faculty members across various academic ranks, ages, and disciplines, with 188 males (47.96%) and 204 females (52.04%) participating.

Convenience sampling was chosen due to accessibility and the voluntary nature of participation. Faculty members were invited via email to complete an online questionnaire hosted on Google Forms. Inclusion criteria required participants to be actively employed academic staff during the data collection period. No specific exclusion criteria were applied, though incomplete responses were omitted from analysis.

2.2. Data Collection Tools

In this study, two instruments introduced in the following section were utilized.

2.2.1. Demographic information form

This form gathered participants' gender, age, academic title, years of professional seniority, type of institution, and duration of AI usage.

2.2.2. Artificial Intelligence Acceptance Scale

Developed by Canan Güngören et al. (2025) was based on Davis's (1989) Technology Acceptance Model, and it comprises 21 items grouped into four dimensions: Perceived Ease of Use [PEU], Perceived Usefulness [PU], Attitude Toward Use [ATU], and Behavioral Intention to Use [BIU]. Following expert evaluation and a pilot study with 400 university students, confirmatory factor analysis [CFA] confirmed the scale's four-factor structure. The model demonstrated good fit indices: RMSEA = 0.058, SRMR = 0.054, χ^2/df = 2.26, AGFI = 0.88, GFI = 0.91, NFI = 0.96, NNFI = 0.98, and CFI = 0.98. Factor loadings were significant, and minor model modifications between certain items further improved fit. The scale's internal consistency was robust, with Cronbach's alpha coefficients of .92 for the overall scale, and subscale alphas ranging from .74 (BIU) to .85 (ATU). Additionally, McDonald's omega values (.79–.86) reinforced the scale's reliability. These findings confirm that the GAIAS is a psychometrically sound instrument for assessing university students' acceptance of generative AI technologies.

2.3. Data Analysis

Data were analyzed using IBM SPSS Statistics 26.0. Descriptive statistics (means, standard deviations) were calculated for all variables. Normality was assessed via Kolmogorov-Smirnov and Shapiro-Wilk tests, revealing non-normal distributions (p < .05); thus, non-parametric tests were employed. Mann-Whitney U tests analyzed group differences for variables with two categories (e.g., gender, institution type), and Kruskal-Wallis tests were used for variables with more than two groups (e.g., age groups, academic titles). Bonferroni corrections were applied for multiple pairwise comparisons to control Type I error. Statistical significance was set at p < .05.

Table 1
Normality Test Results

Academic Staff AI Acceptance Level	*Kolmogorov-Smirnov*[a]			*Shapiro-Wilk*		
	Statistic	df	Sig.	Statistic	df	Sig.
	.083	392	< .001	.957	392	< .001

Since the item scores on the scale range from 1 to 5, higher mean scores approaching 5.00 are interpreted as a high level of acceptance of AI tools, whereas lower mean scores closer to 1.00 indicate a low level of acceptance.

To determine the score range for each response category on the scale, the total score range was divided by the number of response categories, yielding the interval width for each category (Interval width: 4/5=.80). This approach was used to establish the boundaries of the arithmetic mean for each category.

Table 2
Value Range of Arithmetic Means According to the Scale

Response	*Score*	*Score Range*	*Value*
Strongly Disagree	1	1.00 – 1.80	Very Low
Disagree	2	1.81 – 2.60	Low
Neutral	3	2.61 – 3.40	Moderate
Agree	4	3.41 – 4.20	High
Strongly Agree	5	4.21 – 5.00	Very High

3. Findings

3.1. Level of Faculty Members' Acceptance of AI Tools

Table 3 presents the descriptive statistics for the Artificial Intelligence Acceptance Scale and its sub-dimensions among the 392 participating faculty members. The overall AI acceptance score was moderately high, with a mean of 3.61 (*SD* = 0.63) on a 5-point Likert scale, indicating a generally positive perception toward AI tools.

Table 3
The Level of AI Acceptance of Faculty Members

	N	*Minimum*	*Maximum*	*Mean*	*SD*	*Item Count*
AI Tools Acceptance	392	1.19	5.00	3.61	.63	21
Perceived Ease of Use	392	1.00	5.00	3.69	.72	21
Perceived Usefulness	392	1.00	5.00	3.57	.77	21
Attitude Toward Use	392	1.00	5.00	3.43	.71	21
Intention to Use	392	1.00	5.00	3.87	.88	21

Table 3 presents the descriptive statistics for the Artificial Intelligence Acceptance Scale and its sub-dimensions among the 392 participating faculty members. The overall AI acceptance score was moderately high, with a mean of 3.61 (*SD* = 0.63) on a 5-point Likert scale, indicating a generally positive perception toward AI tools.

Among the sub-dimensions, *Intention to Use* exhibited the highest mean score (*M* = 3.87, *SD* = 0.88), reflecting faculty members' strong willingness to adopt AI technologies in their professional activities. This was followed by *Perceived Ease of Use* (*M* = 3.69, *SD* = 0.72), suggesting that participants generally find AI tools accessible and manageable. *Perceived Usefulness* had a mean of 3.57 (*SD* = 0.77), indicating a favorable belief in the practical benefits of AI technologies for academic purposes. The lowest mean score was observed for *Attitude toward Use* (*M* = 3.43, *SD* = 0.71), which, while still positive, suggests some moderate reservations or mixed feelings toward AI adoption.

3.2. Differences in Instructors' Acceptance Levels of AI Tools Based on Independent Variables

3.2.1. Findings by gender variable

Table 4 is a summary of the results of Mann-Whitney U tests comparing AI acceptance scores between male and female faculty members.

Table 4
Mann-Whitney U Analysis Results of Artificial Intelligence Acceptance Scores by Gender

	n	*Mean Rank*	*Sum of Ranks*	*z*	*p*
AI Acceptance					
Female	204	188.89	38533.00	−1.39	.166
Male	188	204.76	38495.00		
Perceived Ease of Use					
Female	204	199.19	40634.00	−.492	.623
Male	188	193.59	36394.00		
Perceived Usefulness					
Female	204	186.23	37990.50	−1.876	.061
Male	188	207.65	39037.50		
Attitude Towards Use					
Female	204	189.98	38755.00	−1.194	.233
Male	188	203.58	38273.00		
Intention to Use					
Female	204	189.84	38727.00	−1.222	.222
Male	188	203.73	38301.00		

As shown in Table 4, no statistically significant differences were observed between genders on the overall AI acceptance scale ($z = -1.39$, $p = .166$). Similarly, subscale analyses revealed no significant gender differences in *Perceived Ease of Use* ($z = -0.492$, $p = .623$), *Attitude toward Use* ($z = -1.194$, $p = .233$), or *Intention to Use* ($z = -1.222$, $p = .222$).

Perceived Usefulness showed a marginally non-significant trend favoring males (mean rank = 207.65) over females (mean rank = 186.23), with $z = -1.876$, $p = .061$, suggesting males may perceive AI tools as slightly more useful, although this did not reach conventional levels of statistical significance.

In general, these results indicate that male and female faculty members exhibit similar acceptance levels of AI tools.

3.2.2. Findings by age variable

Table 5 presents the results of Kruskal-Wallis H tests examining differences in AI acceptance scores across seven age groups.

Table 5
Kruskal-Wallis H Test Results of AI Acceptance Scores by Age

	n	*Mean Rank*	*df*	*Mean*	*p*	*Significant Difference*
AI Acceptance						
25-29	38	223.45	6	13.409	.037*	Ages 35-39 > Ages 45-49
30-34	70	198.90				
35-39	97	217.34				
40-44	79	196.74				
45-49	58	163.66				
50-54	21	159.38				
Over 55	29	177.60				
Perceived Ease of Use						
25-29	38	229.88	6	15.755	.015*	Ages 25-29 > Ages 45-49; Ages 25-29 > Ages over 55; Ages 35-39 > Ages 45-49
30-34	70	195.65				
35-39	97	220.29				
40-44	79	188.46				
45-49	58	167.84				
50-54	21	195.81				
Over 55	29	154.97				
Perceived Usefulness						
25-29	38	218.83	6	7.281	.296	
30-34	70	204.28				
35-39	97	204.70				
40-44	79	196.79				
45-49	58	166.10				
50-54	21	175.12				
Over 55	29	196.53				
Attitude Towards Use						
25-29	38	224.84	6	10.161	.118	
30-34	70	194.26				
35-39	97	210.55				
40-44	79	196.97				
45-49	58	178.80				
50-54	21	143.10				
Over 55	29	190.55				

Table 5 continued

	n	*Mean Rank*	*df*	*Mean*	*p*	*Significant Difference*
Intention to Use						
25-29	38	196.33	6	11.578	.072	
30-34	70	196.41				
35-39	97	218.99				
40-44	79	206.15				
45-49	58	165.57				
50-54	21	158.31				
Over 55	29	184.97				

Significant differences were found in overall AI acceptance ($\chi^2(6) = 13.41$, $p = .037$). Post-hoc analyses indicated that faculty members aged 35–39 had significantly higher AI acceptance scores than those aged 45–49.

Perceived Ease of Use also showed significant age-related differences ($\chi^2(6) = 15.76$, $p = .015$). Younger faculty members aged 25–29 demonstrated greater perceived ease of use compared to those in the 45–49 and 55+ age groups. Additionally, the 35–39 age group reported higher ease of use perceptions than the 45–49 group.

No significant age differences were found for Perceived Usefulness ($p = .296$), Attitude toward Use ($p = .118$), or Intention to Use ($p = .072$), though the latter two approached significance.

These findings suggest that younger faculty members perceive AI tools as easier to use, which may contribute to higher overall acceptance, consistent with research highlighting age-related digital familiarity differences in technology adoption.

3.2.3. Findings by type of institution variable

Table 6 displays the results of Mann-Whitney U tests comparing AI acceptance between faculty members at state (public) and foundation (private) universities.

Table 6

Results of the Mann-Whitney U Test for AI Acceptance Scores Based on Institution Type

Type of Institution	*n*	*Mean Rank*	*Sum of Ranks*	*z*	*p*
AI Acceptance					
State	220	190.48	41905.00	−1.191	.234
Foundation	172	204.20	35123.00		
Perceived Ease of Use					
State	220	175.69	38652.50	−4.134	<.001
Foundation	172	223.11	38375.50		
Perceived Usefulness					
State	220	199.90	43977.00	−.673	.501
Foundation	172	192.16	33051.00		
Attitude Towards Use					
State	220	196.11	43145.00	−.077	.939
Foundation	172	196.99	33883.00		
Intention to Use					
State	220	190.01	41803.00	−1.292	.196
Foundation	172	204.80	35225.00		

No significant differences were found between institution types for overall *AI acceptance* ($z = -1.191$, $p = .234$), *Perceived Usefulness* ($z = -0.673$, p = .501), *Attitude toward Us*e ($z = -0.077$, $p = .939$), or *Intention to Use* ($z = -1.292$, $p = .196$).

However, a significant difference emerged in *Perceived Ease of Use* ($z = -4.134$, $p < .001$), with faculty members at foundation universities reporting higher perceived ease of use (mean rank = 223.11) compared to those at state universities (mean rank = 175.69). This suggests that private university faculty may find AI tools more user-friendly or accessible, potentially reflecting differences in institutional support or infrastructure.

In short, these findings indicate that while acceptance levels are comparable across institution types, perceived ease of use varies, which could inform targeted strategies for AI integration.

3.2.4. Findings by title variable

Table 7 presents the results of Kruskal-Wallis H tests comparing AI acceptance across five professional academic titles.

Table 7
Results of the Kruskal-Wallis H Test for AI Acceptance Scores Based on Professional Title

	n	*Mean Rank*	*df*	*Mean*	*p*	*Significant Difference*
AI Acceptance						
Research Assistant	73	205.14	4	4.74	.315	
Lecturer	115	209.90				
Assistant Prof.	97	178.41				
Associate Professor	67	189.89				
Professor Dr.	40	197.13				
Perceived Ease of Use						
Research Assistant	73	205.34	4	18.95	.001*	Lecturer >
Lecturer	115	226.92				Assoc. Prof.
Assistant Prof.	97	191.02				Lecturer > Prof.
Associate Professor	67	167.32				
Professor Dr.	40	155.06				
Perceived Usefulness						
Research Assistant	73	209.90	4	4.59	.332	
Lecturer	115	198.48				
Assistant Prof.	97	177.53				
Associate Professor	67	196.48				
Professor Dr.	40	212.39				
Attitude Toward Use						
Research Assistant	73	199.01	4	3.52	.474	
Lecturer	115	203.32				
Assistant Prof.	97	180.73				
Associate Professor	67	193.60				
Professor Dr.	40	215.41				
Intention to Use						
Research Assistant	73	200.34	4	3.11	.538	
Lecturer	115	203.25				
Assistant Prof.	97	180.98				
Associate Professor	67	207.33				
Professor Dr.	40	189.58				

According to Table 7, no significant differences were observed in overall *AI acceptance* ($\chi^2(4) = 4.74$, $p = .315$), *Perceived Usefulness* (p = .332), *Attitude toward Use* ($p = .474$), or *Intention to Use* ($p = .538$) among the different academic ranks.

However, *Perceived Ease of Use* showed a significant difference ($\chi^2(4) = 18.95$, $p = .001$). Post-hoc analyses revealed that Lecturers reported significantly higher ease of use perceptions compared to Associate Professors and Professors. This suggests that faculty at earlier career stages may find AI tools more accessible or less complex to use than their more senior counterparts.

On the whole, while acceptance and attitudes towards AI appear consistent across academic ranks, differences in perceived ease of use may reflect varying levels of familiarity or training with AI technologies within faculty career stages.

3.2.5. Findings by years of professional seniority

Table 8 shows the results of Kruskal-Wallis H tests comparing AI acceptance scores across five groups based on years of professional seniority.

Table 8
Kruskal-Wallis H Test Results for AI Acceptance Based on Professional Seniority

Years of Seniority	*n*	*Mean Rank*	*df*	*Mean*	*p*
AI Acceptance					
0 - 5 years	61	175.52	4	6.639	.156
6 - 10 years	88	216.61			
11 - 15 years	108	196.36			
16 – 20 years	58	207.36			
21 years and above	77	182.16			
Perceived Ease of Use					
0 - 5 years	61	208.27	4	5.531	.237
6 - 10 years	88	208.88			
11 - 15 years	108	198.15			
16 – 20 years	58	195.40			
21 years and above	77	171.55			
Perceived Usefulness					
0 - 5 years	61	172.32	4	4.501	.342
6 - 10 years	88	209.98			
11 - 15 years	108	197.73			
16 – 20 years	58	204.95			
21 years and above	77	192.16			
Attitude Toward Use					
0 - 5 years	61	184.10	4	1.922	.750
6 - 10 years	88	202.45			
11 - 15 years	108	197.16			
16 – 20 years	58	208.41			
21 years and above	77	189.62			
Intention to Use					
0 - 5 years	61	165.59	4	9.400	.052
6 - 10 years	88	221.05			
11 - 15 years	108	199.18			
16 – 20 years	58	198.92			
21 years and above	77	187.36			

As can be seen from Table 8, no statistically significant differences were found for overall *AI acceptance* ($\chi^2(4) = 6.64$, $p = .156$), *Perceived Ease of Use* ($p = .237$), *Perceived Usefulness* ($p = .342$), or *Attitude toward Use* ($p = .750$) across seniority groups.

However, the Intention to Use subscale approached significance ($\chi^2(4) = 9.40$, $p = .052$), with faculty members in the 6–10 years seniority range exhibiting higher mean ranks (M rank = 221.05) compared to those with 0–5 years (M rank = 165.59) or 21 years and above (M rank = 187.36). This suggests a potential trend where mid-career faculty show stronger intentions to adopt AI tools than early-career or very senior faculty.

Taken together, these findings imply that professional seniority does not strongly influence faculty acceptance of AI tools, though intention to use may be more pronounced among mid-career academics.

4. Discussion

The findings of this study reveal a generally high acceptance level of artificial intelligence tools among university faculty members, with an overall positive perception across key dimensions of ease of use, usefulness, attitude, and intention to use. This supports previous research demonstrating favorable faculty attitudes towards AI integration in higher education (Slimi, 2022; Vera, 2023). Faculty members in this study showed the strongest scores in their intention to use AI technologies, reflecting a willingness to incorporate these tools professionally, consistent with findings obtained by Runge et al. (2025) and Li (2023).

Gender was not found to significantly influence AI acceptance levels, corroborating studies from Poland and Egypt (Strzelecki & El Arabawy, 2024) and Egypt (Ragheb et al., 2022). However, more nuanced research highlights gender differences in technology-related anxiety and enjoyment, with women typically reporting higher anxiety and lower enjoyment than men (Zhang et al., 2023). Tang et al. (2025) further identified that male academics tend to use generative AI tools more frequently and achieve higher productivity, indicating that gender may shape the manner and extent of technology utilization rather than acceptance alone. Barriers such as limited access and distrust among women users further compound these differences (Tarhini et al., 2014).

Age differences emerged prominently, with younger faculty members aged 25–29 and 35–39 demonstrating higher acceptance and perceived ease of use compared to their older colleagues aged 45 and above. This aligns with literature indicating greater AI-related anxiety among older individuals (Liang & Lee, 2017) and a general decline in technology acceptance with increasing age (Ragheb et al., 2022; Zaid et al., 2022). The increased digital literacy and familiarity among younger faculty likely underpin these findings.

The type of institution (state versus foundation) did not significantly impact overall acceptance, supporting Al Darayseh's (2023) findings that institutional context and professional seniority are not major determinants of AI acceptance in academic settings. Nevertheless, sector-specific studies such as Hamedani et al. (2023) indicate institutional differences in AI acceptance, especially in healthcare, underscoring the influence of organizational culture and resource availability.

Professional title and years of seniority showed no significant effect on AI acceptance, mirroring Zhang et al. (2023) and Al Darayseh (2023) who reported that acceptance is more strongly linked to perceived ease of use and usefulness rather than rank or tenure. Although instructors showed slightly higher perceived ease of use compared to senior faculty, this difference was not statistically significant. The trend towards higher intention to use AI among mid-career faculty suggests a possible balance between openness and experience that merits further exploration.

Overall, the findings reaffirm the applicability of the Technology Acceptance Model (Davis, 1989) in understanding AI adoption among university faculty, highlighting perceived ease of use and usefulness as pivotal factors. These results underscore the importance of developing targeted training and support systems, especially aimed at older and senior faculty members, to foster broader AI adoption and integration in higher education.

5. Conclusion

This study demonstrated that university faculty members generally hold positive attitudes toward artificial intelligence tools, with high acceptance across dimensions of ease of use, usefulness, attitude, and intention to use. Younger and mid-career faculty exhibited higher acceptance and perceived ease of use, while gender, institution type, professional title, and years of seniority showed limited influence on acceptance levels.

These findings suggest that universities aiming to promote AI integration should focus on enhancing usability and providing tailored support, particularly for senior and less digitally familiar faculty. Overall, the results offer valuable insights into faculty perceptions of AI, contributing to effective strategies for advancing AI adoption in higher education settings.

6. Implications of the Study

The findings of this study have important implications for higher education institutions seeking to promote the integration of artificial intelligence technologies among faculty members. The generally high acceptance levels suggest a readiness among academic staff to adopt AI tools, which institutions can leverage by providing targeted training programs focused on enhancing ease of use and perceived usefulness. Special attention should be given to older and senior faculty members who may experience more challenges with technology adoption. Additionally, differences observed by institution type in ease of use highlight the need for equitable resource allocation and technological infrastructure across universities. From a theoretical perspective, this study reinforces the applicability of the Technology Acceptance Model in the context of AI adoption in academia and suggests avenues for future research to explore additional factors such as ethical concerns, trust, and cultural influences.

7. Limitations of the Study

This study has several limitations that should be acknowledged. First, the research was conducted with a limited number of faculty members; future studies could involve a larger and more diverse sample across multiple universities nationwide to better capture faculty perspectives on AI acceptance. Such a comprehensive study could potentially be undertaken by national bodies such as the Higher Education Council.

Second, comparative studies at the faculty and department levels are needed to explore which academic fields and purposes most commonly involve the use of AI tools.

Third, in-depth qualitative research with faculty members in older age groups could provide a more nuanced understanding of their perceptions regarding AI acceptance and identify activities that could positively influence these perceptions.

Fourth, focused analyses on associate professors and professors could help uncover their specific concerns and barriers to using AI technologies. Such studies would contribute to a deeper comprehension of this group’s attitudes and anxieties toward AI adoption.

Fifth, developing and evaluating AI-integrated programs and best practice models at the faculty and department levels within higher education would be valuable to assess their effectiveness and scalability.

Finally, research examining negative perceptions of AI is also needed. Following such investigations, faculty members could be better informed about both the advantages and disadvantages of AI, supporting more balanced and informed acceptance.

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Data availability: The data underlying this study is not publicly available due to confidentiality agreements and ethical considerations. However, de-identified datasets may be shared upon reasonable request from the corresponding author, subject to approval from the relevant ethics committees. Researchers interested in accessing the data can contact Selçuk Bilgin at selcuk.bilgin@ozyegin.edu.tr for further inquiries.

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Ethics statement: This study was conducted in compliance with ethical standards and received approval from two institutional ethics committees. Ethical approval was granted by Sakarya University Educational Research and Publication Ethics Committee (Approval Number: 27/42, Date: 10.01.2024) and Özyeğin University Human Research Ethics Committee (Approval Number: 2024/04/02, Date: 26.02.2024). Participants were informed about the study's objectives, procedures, and their rights before taking part. Written informed consent was obtained, ensuring voluntary participation and the right to withdraw at any time. Additionally, participants consented to the publication of findings while maintaining anonymity and confidentiality in accordance with ethical research guidelines.

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